NUI Galway
OÉ Gaillimh

Socio-Economic Marine Research Unit

The Socio-Economic Marine Research Unit (SEMRU)
National University of Ireland, Galway

Working Paper Series

Working Paper 19-WP-SEMRU-05

Estimating the value of achieving good ecological status across Irish water catchments using value transfer

Stephen Hynes and Cathal O'Donoghue

If referencing please cite the final published article based on this working paper: Hynes, S. and O'Donoghue, C. (2020). Value transfer using spatial microsimulation modelling: Estimating the value of achieving good ecological status under the EU Water Framework Directive across catchments. Environmental Science and Policy, 110, 60-70

Whitaker Institute

For More Information on the SEMRU Working Paper Series
Email: stephen.hynes@nuigalway.ie, **Web:** www.nuigalway.ie/semru/

19-WP-SEMRU-05

SEMRU *Working Paper Series*

Estimating the value of achieving good ecological status across Irish water catchments using value transfer

Stephen Hynes and Cathal O'Donoghue

Socio-Economic Marine Research Unit (SEMRU), Whitaker Institute, National University of Ireland, Galway

Abstract

There has been considerable debate over the robustness of value transfer methods for environmental policy evaluation. The empirical findings regarding the transfer validity of such methods have been particularly mixed. This paper presents a novel value transfer approach that uses spatial microsimulation in the value function transfer. The results of a contingent valuation exercise that estimates the value to the Irish general public of achieving good ecological status, as specified in the Water Framework Directive, are transferred to a spatial microsimulation population within individual water management units (WMUs) across Ireland. The welfare estimates from this value function based transfer approach are compared against the results from previous primary valuation studies in one of the WMUs and transfer errors are found to be low. The proposed spatial microsimulation value transfer approach controls for the heterogeneous distribution of populations across the WMUs. It also controls for the fact that the willingness to pay will vary according to an individual's geographic proximity to the water body within each catchment and with the current ecological status of the WMU.

Key words: Contingent valuation, EU Water Framework Directive, good ecological status, value transfer, spatial microsimulation modelling

Acknowledgements

This study was funded under the EPA Research Programme 2014–2020. The programme was financed by the Irish Government. It is administered on behalf of the Department of Communications, Climate Action and Environment by the EPA, which has the statutory function of co-ordinating and promoting environmental research.

Corresponding author email address: stephen.hynes@nuigalway.ie

1. Introduction

The primary aim of the EU Water Framework Directive (WFD) was the establishment of integrated catchment management plans for the protection of inland surface waters, transitional waters, coastal waters and ground waters. Under the directive EU Member States are required to conserve and restore their waterbodies to 'good ecological status' (GES) by 2027. The Directive runs in 6-year cycles and the EU member States are currently in the second cycle that runs from 2016 – 2021. The WFD adopted an over-arching ecosystem approach to water management and was a move away from almost 30 years of previous European water legislation (such as the Bathing Water Directive (76/160/EEC), the Urban Waste Water Treatment Directive (91/271/EEC), the Drinking Water Directive (98/83/EC) and the Nitrates Directive (91/676/EEC)), that tackled individual water quality issues connected with public health or pollution emanating from sources such as urban wastewater and agricultural operations. The earlier legislation also relied on fewer water quality indicators[1].

As is the case for many EU Member States, against a backdrop of increased anthropogenic pressures driven by an expanding population and a fast growing economy, improving or even maintaining satisfactory status in Irish water bodies is difficult and costly. The latest water quality monitoring figures in Ireland, for the period 2013 to 2018, suggest that 52.8% of surface water bodies assessed were in satisfactory ecological health, having either good or high ecological status (EPA, 2019). The remaining 47.2% of surface water bodies were judged to be in moderate, poor, or bad ecological status. The waterbodies satisfactory status has fallen slightly since the previous assessment period of 2010 – 2015 when it stood at 55.4%[2].

Given the costs involved in trying to maintain, and improve standards through the integrated catchment plans an important policy question is whether the benefits to

[1] For a comprehensive overview of the policy transition towards the WFD in the EU the interested reader is directed to Giakoumis and Voulvoulis (2018).

[2] Ecological status assessment is underpinned by research and data relating to many physical, chemical, and biological quality elements. In the Irish case this involves the assessment of biological and environmental data collected from 2,703 surface water bodies. The complexity in deriving an overall status measure from these different types of data has been widely debated in the literature. It has been shown for example that the choice of the aggregation method used to combine the different data sources into an overall assessment can considerably affect the assessment outcome (Langans et al. 2014) while Beniston et al. (2012) argued that there was a need to understand how climate change affects the ecological thresholds used to set WFD targets.

society of achieving GES outweigh the costs of the monitoring and management involved. Indeed, an important element of the EU WFD is the requirement to take into account the economic costs and benefits of achieving improvements to ecological status in catchment management plans, along with the introduction of full social cost pricing for water use. Hence, benefits play an important role in the assessment of the proportionality of costs in the implementation of the WFD. Under the directive a member state must prove disproportional costs if they are to be granted derogations in terms of postponing the achievement of targets beyond the set dates for any given management unit. This implies that the costs must outweigh the benefits of achieving the targets on time, which requires the estimation of the benefits to society of achieving the goals of the directives.

Non-market valuation methods can be used to identify the benefits that society derives from achieving GES targets across individual management areas. However, carrying out primary valuation across the many regional water catchments is costly and time consuming. Indeed, in the case of the WFD, it has been suggested that there are too many water bodies and too little time in which to undertake a primary valuation study to decide if there are disproportionate costs in achieving good ecological status (Hanley et al., 2006a). A recent EU report also noted how “Ireland applied no exemptions on the grounds of disproportionately expensive measures [during the first 6 year cycle] because no economic analysis was undertaken to support such exemptions” (EU Environment, 2015).

In Ireland alone there were 151 water management units (WMUs[3]) under the first cycle of the WFD where the target of achieving good ecological status has been set and only one primary valuation in one catchment has been undertaken (Stithou et al., 2012). Rather than relying on primary valuation studies that directly estimate the benefit value of achieving the targets set within a catchment, value transfer methods have being considered. Value transfer is the application of values estimates from past research to assess the value at other ‘policy’ sites where little or no data is available in

[3] A water management unit is a geographical sub unit of a river basin district consisting of a number of water bodies relevant to a particular subcatchment. It was the standard unit of management under the first cycle of the WFD management in Ireland and is therefore what is used in the analysis presented here. For the second cycle the standard sub units are catchments and subcatchments, of which there are 46 and 583 respectively.

relation to benefit values (Rosenberger and Loomis, 2000; Loomis 1992; Rosenberger and Loomis, 2003; Rosenberger and Stanley, 2006). In the United States, the US Environmental Protection Agency have relied heavily on this extrapolation of non-market valuation estimates from previous studies to estimate benefits for new policy scenarios in its environmental policy benefit cost assessments but this has not generally been the case in Europe (Newbold et al. 2018).

Integrated management approaches aimed at achieving GES across many management units need to be adaptive, and should therefore be able to combine the comprehensive biological and environmental monitoring data required to assess GES with data on public preferences that could produce societal benefit estimates in a timely manner facilitating potentially worthwhile changes in policy implementation where needed. Existing approaches to value transfer are not generally able to adapt to such complex circumstances. In this paper however we propose a novel transfer methodology that is adaptive in the sense that it allows for the calculation of value estimates across water management units that vary in their base line quality condition, both across units and within units over time, and which can be quickly changed to generate estimates at different water management spatial scales.

There are three main approaches to value transfer (VT): (i) the transfer of the mean value from the original research (ii) the transfer of an adjusted mean value from the original research (usually adjusted for differences in income between original and policy studies) and (iii) the transfer of a complete value function. While the first approach assumes similarity in the environmental good and the socio-economic characteristics between the study and target site, the other two approaches attempt to adjust the mean values transferred and re-calculate it respectively, in order to account for differences between studies in terms of environmental characteristics and/or socioeconomic characteristics.

Value function transfer involves the use of a valuation function to calibrate the value being transferred from the original research according to specific physical and demographic characteristics of the policy site. Though the literature is generally in agreement that similarity between the original study and the policy study under review is an important factor in assuring transfer validity (Navrud and Ready, 2007 and Norton and Hynes, 2018), function transfer has the potential to relax the degree of similarity necessary for transfer of values by allowing for differences in site and population characteristics to be taken into account by the valuation function. However, function transfers are "limited by quality and availability of primary research, limited consensus on performance and validity of types of function transfers and lack of consensus on how to generate functions" (Rosenberger and Johnston, 2009). Furthermore, the value function approach may still not have information at the necessary scale to control for factors such as environmental quality differences, income and cultural differences and extent of the market (Johnston et al. 2015; Johnston and Thomassin, 2010; Hynes et al. 2010; Navrud and Ready, 2007). That said, the general consensus within the literature would seem to be that function transfers generally outperform unit transfers (Schmidt et al., 2016; Johnston and Rosenberger, 2010; Rosenberger and Stanley, 2006).

Another necessary condition for valid value transfer, even in the case of the value function approach, is 'commodity consistency'. As discussed by Boutwell and Westra (2013), a transfer of benefits cannot be valid if the construct under investigation differs from study site to policy site. According to the authors a seemingly simple requisite for valid transfer, securing commodity consistency, can become problematic because of the nature of non-market environmental goods. The heterogeneity of some environmental goods, such as in our case, water quality in catchments, presents a challenge with respect to acquiring sufficient primary study data that satisfies the requirement for commodity consistency. Ideally, if the researcher wishes to transfer past estimates of the value of good water quality from one catchment to another then she should control for the fact that water "quality" could be defined differently by different studies.

The main strategies adopted in the literature for dealing with commodity consistency is simply to ensure that value transfer is only applied where the policy and study sites are very similar or it has also been argued that the use of meta-analysis value function approach that uses regression methods to examine the influence of study and site specific characteristics on estimated WTP among a collection of relevant primary studies can control for underlying differences in the environmental good being examined across the studies and policy site (Brouwer et al., 2008; Hynes et al., 2018).

In this paper the proposed transfer methodology directly controls for commodity consistency in the function that estimates the value of achieving GES. This is achieved by ensuring the differences in the current status is explicitly controlled for in the value function itself and also across the study and policy sites. Following the suggestions of Bateman et al. (2011) distance to the environmental good (the water body) is also included as an explanatory variable in our function and controlled for in the transfer process.

Furthermore, we do not just multiply our function coefficients by summary statistics at the policy site but follow Hynes et al. (2010) by using a spatial microsimulation modelling framework. Value transfer of this type is akin to using a regression based statistical matching methodology (D'Orazio et al., 2006). In particular, we transfer our stated preference contingent valuation function to a synthetic population that has been derived through the statistically matching of a national survey and Census of Population small area statistics (the SMILE Model). This match produces small area population micro data estimates for the year 2014 using a combinatorial optimization technique. This approach allows us to efficiently transfer the value function to a particular region (or water management unit) of interest that accounts for the heterogeneity in the characteristics of the populations between study and policy sites at an individual level. This new approach to value transfer is something that can be replicated elsewhere due to the widespread development of spatial microsimulation models across a number of countries.

In what follows we first briefly review past efforts at using value transfer for estimating water quality improvements. Section 3 then presents the design of the contingent valuation survey used as a case study. Section 4 presents the transfer methodology that is applied in order to estimate average and aggregate values to residents of achieving good ecological status across catchments. This section also introduces the combinatorial optimization process used to generate the synthetic population that the value function is transferred to. Model results and the transferred willingness to pay (WTP) estimates are presented in section 5. Finally, section 6 concludes with some recommendations for further research.

2. Value Transfer for water quality improvements

There have been a number of studies that have used value transfer in the context of estimating the value of water quality improvements at different spatial scales. One of the earliest studies to examine the issues encountered in using existing studies to measure the benefits of water quality improvements was undertaken by Desvousges et al. (1992). Their research indicated that although value transfer offered promise, the fact that the existing studies at the time were not designed with transfer in mind, in the authors' opinion, placed severe limitations on the effectiveness of any transfer undertaken. This sentiment continues to be expressed with a recent paper by Hynes et al. (2018) going as far as to advocate that, due to publication selection bias, where journals have a preference for reporting novel methods, the basic forms of each valuation model type should be supplied with any valuation exercise published (e.g. a conditional logit specification for choice experiments with associated WTP values) for use in possible meta-analysis value transfer as this could be a result in more reliable transfer estimates being generated.

A number of studies have examined the possibility of applying value transfer in the context of the WFD (Ferrini et al., 2014; Hanley et al. 2006a and 2006b; Hasler et al. 2012; Bateman et al. 2011, Norton and Hynes, 2015). Hasler et al. (2012) carried out a stated preference study in Odense Fjord and Roskilde Fjord that was used to test the transfer of unit values as well as the whole value functions between these two Danish fjords. The results indicated that the value transfers between the two fjords resulted in very low transfer errors, and the authors concluded that this result was promising for the use of value transfer in WFD implementation. The application of value transfer in the context of the WFD has also been examined and tested in Hanley et al. (2006a, 2006b) by applying the same choice experiment (CE) in two similar rivers and then testing the transfer of one of the river value functions to the other and visa versa. In an Irish context, Norton et al. (2012) examined the possibility of using the Stithou et al. (2012) Boyne catchment benefit estimates (derived from a choice experiment study of the population in that catchment) in a value transfer situation for Irish water bodies but found the average transfer errors to be high (58%) from the primary site to other river catchments.

In Hanley et al. (2006a) the authors tested for the equality of parameters and WTP values across the original and transferred functions. Preferences and values were found to differ significantly across the two samples which in turn meant that the hypothesis of equality of parameters and WTP values were rejected. Hanley et al. (2006b) also estimating the welfare benefits of water quality improvements under the WFD and tested the transferability of these improvement value estimates for two small water catchment areas in Eastern Scotland with poor ecological status. The authors estimated a Random Parameter CE Model with independent and correlated preferences. In terms of value transfer tests it was found that the estimated implicit prices for the river quality attributes in the model on the whole were transferable across catchments based on a test for differences in compensating surplus estimates and the alternative equivalence test (Kristofersson and Navrud, 2005). The authors suggested that policy makers should proceed with caution in transferring value estimates for water quality improvements under the WFD.

Another application of value transfer in the context of water quality is that of Iovanna and Griffiths (2006). This study examined the use of value transfer methods to estimate ecological benefits as part of the total benefits assessment analysis for seven Environmental Protection Agency (EPA) rules issued under the Clean Water Act in the USA. Furthermore, Morrison and Bennett (2004) ran seven choice modelling applications designed to value improved river health in New South Wales. The resulting welfare estimates were used in a value transfer exercise to value improvements in the health of other rivers within the state. Significant differences were revealed between the majority of implicit prices for the within-catchment samples compared to out-of-catchment samples which did not reveal any difference.
Elsewhere, Morrison et al. (2002) examined the validity of value transfer for two Australian wetlands in a CE context and found mixed results. The estimated benefit functions of the two sites differed while the estimated implicit prices showed insignificant differences for 6 of the 8 implicit prices considered. In earlier research, Bergland et al. (1995) tested the transfer of WTP values for water quality improvement using two similar water courses at the same point in time and with the same estimation methods. In a similar warning as Hanley et al (2006b) the significant differences found in the value functions resulted in Bergland et al. (1995) concluding

that any transfer of benefit values and/or functions between sites should be undertaken with extreme caution.

At an international level, Bateman et al. (2011) developed principles for the appropriate specification of transferable value functions arguing that these should be developed from theoretical rather than ad-hoc statistical approaches. They argue that the crucial principle determining methodological appropriateness of the value transfer approach to be used concerns the degree of heterogeneity between the various sites across which the transfers are to take place. They note that when dissimilar sites are involved the value function approach has the ability to adjust for physical or socio-economic/demographic differences whereas simple mean value transfers will be unable to account for such differences and will generally yield larger errors than value function approaches. Another key principle offered is that the value functions need to be specified for the purposes of transfer between study and policy sites rather than for obtaining statistical best-fit at study sites alone pointing to the fact that an over-parameterised model is likely to perform better in-sample but will likely produce poor predictive values out-of-sample. A third principle highlighted by the authors is that the specified value transfer function must include predictors that are of generic relevance to both study and policy sites. These principles are taken on board with the methodological approach used in this paper.

Also at an international level, a recent study by Czajkowski et al. (2017) investigated the performance of international benefit transfer using data from identical and simultaneous contingent valuation studies on marine water quality in nine European countries surrounding the Baltic Sea. Their analysis found that while different functional forms may offer improvements in model fit, this does not automatically mean improvements in transfer errors or minimum tolerance levels. Johnson et al. (2008) also employed value transfer in a stated preference study in England and Wales in order to calculate public WTP for a reduction in risk of illness resulting from swimming in contaminated river waters in Scotland. Similar to Hynes et al. (2013), the study was framed in the context of the EU Bathing Waters standards.

The application of transfer approaches in the context of water quality improvement benefit value estimation has been limited mainly due to the differences between study and policy sites in terms of the relevant populations, the quality of the water bodies and even in the case of international value transfer differences in the way that water quality is measured between sites. This paper aims to resolve these issues and add to the value transfer literature more generally by developing a transfer approach that controls for the heterogeneous distribution of populations across catchments and for the fact that the willingness to pay will vary according to an individual's geographic proximity to the water body within each catchment. Unlike previous research the method developed in the paper also explicitly deals with the issue of 'commodity consistency' in the transfer process as the current ecological status of the water catchment is controlled for in the transfer function.

3. Survey Design and Contingent Valuation Method (CVM) Question

In order to test the use of spatial microsimulation modelling for value transfer, data from a survey of the Irish public carried out in 2012 is employed. The survey was administered to obtain information relating to the Irish publics' preferences for quality improvements to Irish water bodies in line with requirements laid down by the WFD and, in particular, to estimate the public good benefit value for residents of WMUs resulting from achieving good ecological status within their catchment as prescribed in the WFD a household survey was carried out. The input of three focus groups was first necessary to identify the aspects of the river's ecological status that are important to both experts in the field and to the general public.

The first focus group was organised with eight experts; river managers, water management consultants and ecologists who were directly involved in developing catchment management plans. The overall aim of the experts focus group was to help shape the agenda for the latter two focus group discussions with the general public and to identify a preliminary set of important features associated with the achievement of 'good ecological status' that might be used in the CVM description. The second and third focus groups involved a group of 8 and 12 individuals respectively from two different catchments. The capability of participants to answer the draft questions were examined as well as the relevance of the key water body features identified for inclusion in the CVM question. The latter two focus groups also served to derive values for the price range to use in the CVM payment card.

Following the completion of the focus groups, a pilot survey was finalised and tested on a sample of 50 individuals in the months prior to the main survey. A market research company was employed to carry out both the pilot and main surveys. Along with observations from earlier focus group discussions, results from the pilot were used to refine the questions asked in the main survey. The market research company followed a quota control sampling procedure to ensure that the survey was nationally representative for the population aged 18 years and above. The quotas used were based on known population distribution figures for age, sex and region of residence taken from the Irish National Census of Population, 2011. Interviewers from the survey company collected the data face-to-face with respondents in their home. They were instructed to go through the survey carefully with respondents to ensure that they fully understood what was required of them. As is standard for household level surveys of this type only one individual was interviewed per house. Eight hundred and fifty three interviews were completed.

In the final survey instrument, respondents were asked questions related to their attitudes toward various ecological features associated with water bodies and questions related to their use of different types of water bodies. Socio-demographic questions were also asked related to age, gender, marital status, occupation, working status, income, number of persons in household and education. Finally, a contingent valuation method (CVM) based question was asked of respondents that examined their WTP to achieve 'good ecological status' across the entire catchment in which they reside. For the CVM question, respondents were first informed that: "The European Water Framework Directive requires that all Irish water bodies meet a standard of Good Ecological Status by 2015. This will mean that the water catchment in which you currently live [*at this point the respondent was informed of the name of the Water Management Unit in which they lived*] will have:

- A healthy aquatic ecosystem (fish, insects, plants, wildlife on the shoreline or banks at good status)
- Good water clarity and smell
- Low levels of erosion of the banks (the possibility of an extreme flooding event will be at most once every 20 years)"

The choice of the above characteristic in the CVM question description was informed by the focus group discussions but also by prior choice experiment valuation study carried out in the Boyne Catchment by Stithou et al. (2012).

The respondent was then informed what the average status of the water quality in their local water management unit area was in the previous year based on the EPA's water quality monitoring system that rates water bodies based on parameters indicative of biological quality elements, hydromorphological quality elements and physico-chemical quality elements. In particular, they were informed what percentage of the WMU was rated as poor, moderate and good according to the EPA monitoring data. For the period under analysis, 47% of rivers, 57% of lakes and 55% of transitional waters required improvements to achieve satisfactory (good or high GES) status (EPA, 2015).

The respondent was then asked to consider what is the maximum amount they would be willing to pay to get their local water body to a point where it has reached 100% Good Ecological Status? They were informed that the payment would be an annual increase in income tax for them personally to be paid for 10 years and that it would be ring fenced for funding improvements in just this catchment system.

Respondents were also asked to remember that many people say they are willing to pay more in these surveys than they actually would if the situation was real. They were therefore encouraged to consider fully how improvements in the ecological status of their local river or lake would benefit them before answering and to actually imagine paying the specified amounts for the next 10 years.

Individuals in the survey were then asked the following question:
"Which of the following amounts is the maximum amount that you would be prepared to pay per year for 10 years to get your local water body to a point where it has reached 100% Good Ecological Status?"

Respondents were then presented with a payment card showing 25 bid amounts ranging from €0 to €200. Each respondent chose the bid amount that represented their maximum WTP. This bid value was used as the dependent variable in the CVM model. Following Cameron and Huppert (1989), the response is interpreted not as an exact statement of WTP but rather as an indication that the WTP lies somewhere between the chosen value and the next larger value above it on the payment card. In this questionnaire the price range used in the payment card was based on the responses to the pilot study which utilized the open-ended elicitation format (see Haab and McConnell, 2002). Applications of the payment card method in the literature include Ryan and Watson (2009), Hynes and Hanley (2009) and Czajkowski et al. (2017). The main advantages and disadvantages of the payment card format as opposed to other methods aimed at eliciting WTP are not reviewed here but are discussed in more depth by Boyle et al. (1997), Blamey et al. (1999), Boyle (2003) and Fonta et al. (2010).

4. Methodology

There are a number of steps involved in the transfer process used to estimate the average and aggregate value to residents of achieving good ecological status across the WMUs. Firstly, we estimate a CVM model using the responses to the CVM question from the nationwide survey. This provides an estimate of WTP to achieve good ecological status (GES) for each individual in our sample. Secondly, we apply the model coefficients to a microsimulated population that is representative at a low spatial level (the Electoral District (ED) level of which there are 3400 in Ireland). Finally, in a geographical information system, we overlay the EDs on the WMUs to generate average and total WTP values for each catchment. This methodology allows us to take into account the spatial heterogeneity of the target population and the water body qualities in each WMU in the WTP aggregation process. Each step of the process is expanded upon below.

The Contingent Valuation Model.

Following Hynes and Hanley (2009) and Buckley et al. (2012) the WTP responses to the CVM question outlined in the previous section was treated in a parametric model, where the WTP value chosen by each respondent was specified as: $WTP_i = \mu_i + \varepsilon_i$. where μ_i is the deterministic component and ε is the error term. It is assumed that $\varepsilon \sim N(0, \sigma^2 I)$. As mentioned previously, the respondent's chosen bid value is interpreted as an indication that the WTP lies somewhere between that value and the next larger value above it on the payment card. Therefore, the Generalized Tobit Interval model is employed as it has a log-likelihood function adjusted to make provision for the point, left-censored, right-censored (top WTP category with only a lower bound) and interval data from the payment card choices. For individuals $i \in C$, we observe WTP_i, i.e. point data and for respondents $i \in L$, WTP_i are left censored. Individuals $i \in R$ are right censored; we know only that the unobserved WTP_i is greater than or equal to WTP_{Ri}. Finally respondents $i \in I$ are intervals; we know only that the unobserved WTP_i is in the interval $[WTP_{1i}, WTP_{2i}]$. The log likelihood is given by:

$$\ln L = -\frac{1}{2}\sum_{i \in C} w_i \left\{ \left(\frac{WTP_i - x\beta}{\sigma} \right) + \log 2\pi\sigma^2 \right\} + \sum_{i \in L} w_i \log \Phi \left\{ \left(\frac{WTP_{Li} - x\beta}{\sigma} \right) \right\}$$
$$+ \sum_{i \in R} w_i \log \left\{ 1 - \Phi \left(\frac{WTP_{Ri} - x\beta}{\sigma} \right) \right\} + \sum_{i \in I} w_i \log \left\{ \Phi \left(\frac{WTP_{2i} - x\beta}{\sigma} \right) - \Phi \left(\frac{WTP_{1i} - x\beta}{\sigma} \right) \right.$$

where Φ () is the cumulative distribution function of the normal distribution, respectively, and w_i is the weight of the *i*th individual and $x\beta$ represents the vector of parameters *x* and their associated coefficients β in the chosen model. Since our data is unweighted, w_i is simply set equal to 1. The Generalized Tobit model assumes normality of the error terms. Since we wished to use the parameter estimates from the model for a value transfer exercise using a simulated population for each of the WMUs the model specification included mainly variable that would also be in our simulated population dataset. In our chosen model:

WTP = f (Gross income, Gender, third level education, married, have visited local water body in last 12 months, rural resident, unemployed, foreign national, distance to nearest water body and the ratio of the percentage of Good to Poor/Moderate water quality rating in the respondents local water body).

The expectation are that the models results would indicate a positive relationship between income level and WTP. Similarly it would be expected that those with third level education would be better informed on the value of high water quality and would show a higher WTP. There is a reasonable expectation that the ratio of the percentage of Good to Poor/Moderate water quality in the catchment would be negative indicating that people would be willing to pay more for a larger improvement although the opposite has also found to be the case (Soliño et al., 2013). A positive relationship would also be expected between WTP and those who have visited the catchment in the last 12 months while there is a reasonable expectation that there would be a negative relationship between WTP and distance to the nearest water body in the catchment and between being unemployed and WTP. There was no prior expectations on the possible sign for the gender, being married, being a rural resident or foreign national.

Only the dummy variable "*have visited local water body" in last 12 months* was not available for the simulated population observations that we use in the transfer exercise. To deal with this we estimated a simple logit model to predict whether a person is likely to have visited their local water body as a function of socio-demographic characteristics and using the parameters from this model generate a 0/1 estimate for the simulated population observations across the WMUs. While more complex model specifications could have been employed for the CVM function we used the generalized tobit as specified above as the same model was used in a previous CVM study in one of the WMUs that we can directly compare our model results to. This is an important check of the transfer validity of our spatial microsimulation value transfer approach.

The simulated population dataset from a spatial microsimulation model

When statisticians draw samples from a given population, such as members of the public or land owners, they may have the age, gender, region or farm size and farm system profiles of the individuals. If such information is available, including it at the sampling stage will lead to more efficient designs (Kolenikov, 2014). In this case unequal probabilities of selection can be controlled for with probability weights. If on the other hand this information is not available in the sample but is known for the population of interest (for example there may be census totals of the age and gender distribution available) it is still possible to use this information by generating weights such that the reweighted data conforms to these known figures. A number of alternative mechanisms have been previously been employed for generating these weights when creating spatial micro data. These include using a generalised regression based reweighting method (Lehtonen and Veijanen, 2009), multi-dimensional Iterative Proportional Fitting (IPF) (Ballas et al., 2007), linear programming methodologies (Clancy et al. 2012) and the aforementioned simulating annealing approach described by Hynes et al. (2010). IPF is one of the most common weight-calibration procedures and has been applied extensively for spatial microsimulation analysis (Deville et al. 1993; Deming and Stephan, 1940; Norman, 1999; Tanton and Edwards, 2013). Standard routines are now also available in statistical software packages that allow the researcher to apply this routinely[4]. Lovelace et al. (2015) evaluating the performance of IPF for spatial microsimulation and conclude that the results are sensitive to initial conditions, notably the presence of 'empty cells', and the dramatic impact of software decisions on computational efficiency.

Spatial microsimulation models contain geographic information that links microdata with a specific location and can therefore facilitate a very local approach to policy analysis (O'Donoghue et al. 2015). Hynes et al. (2010) previously pointed out that the spatial scale at which environmental valuation studies are carried out is often national and will not be regionally representative. The authors suggested that one could improve the relation between the sample and the regional population of interest in a value transfer exercise by adjusting the weights of the cases in the sample so that the marginal totals of the adjusted weights on specified characteristics agree with the corresponding totals for the regional population. Hynes et al. (2010) employed the combinatorial optimization technique known as simulated annealing (SA) in a WTP aggregation exercise to re-weight a nationally representative environmental valuation microdata sample to fit small area population (SAP) statistics. Similarly, Cullinan et al. (2011) used the same technique with a revealed preference dataset of woodlands recreationalists to demonstrate how travel cost models, estimated using on-site survey observations could be used to predict demand at alternative policy sites.

Rather than directly reweight the CVM sample to fit the small area population statistics, as was done by Hynes et al. (2010), we take an existing spatial simulated population and apply the coefficients from our CVM model to estimate the average and total WTP in each WMU based on the simulated population's characteristics in each of the WMUs. The simulated population is taken from SMILE (Spatial Microsimulation Model for Irish Local Economy) which is a static spatial

[4] The Stata command 'ipfraking' for example performs IPF to produce a set of calibrated survey weights such that the sample weighted totals of control variables match the known population totals (Kolenikov, S., 2014).

microsimulation model designed to simulate regional welfare, income, and labour distributions in Ireland and thus provide a basis for regional economic analysis (O'Donoghue, 2014). The SMILE model uses a combinational optimisation technique called quota sampling to statistically match the 2012 sample from the Survey on Income and Living Conditions (SILC)[5] to small area population statistics from the Census of Population 2011. This generates a simulated dataset containing all the variables from SILC for the complete population of Ireland. Importantly the simulated observations in this new micro-dataset is representative of the small areas (the 3409 Electrical Districts (EDs[6]) in Ireland) through the constraints of gender, education, age and ED population totals.

The quota sampling procedure analyses individuals grouped into households against constraints at either the individual or household level. Similar to the simulating annealing matching approach used by Hynes et al. (2010), quota sampling selects observations from a sample at random and considers whether they are suitable for admittance to a given small area population based on conformance with aggregate totals for each small area constraint. Unlike simulating annealing, Quota Sampling only assigns individuals that conform to aggregate constraint totals and once an individual is deemed selected, it is not replaced. To accommodate this, small area aggregate totals for each constraint variable are designated as the initial values for what are termed 'quotas'. These quotas may be considered as running totals for each constraint variable, which are recalculated once a household is admitted to a small area population within the microsimulation process. This procedure continues until the total number of simulated units is equal to the small area population aggregates (i.e. all quotas have been filled). The combinatorial optimization process conducted for SMILE produces 4,327,959 individual records made up of the 11,557 records in the original SILC survey.

Validation techniques are then used to ensure the synthetically created data are in line with various regional benchmarks for the variables used as constraints in the

[5] The Survey on Income and Living Conditions (SILC) in Ireland is a household survey covering a broad range of issues in relation to income and living conditions. It is the official source of data on household and individual income in Ireland.
[6] EDs are used by the Central Statistics Office (CSO) as the basic political jurisdiction unit within the state. Population statistics from the Census of Population are available down to this level.

simulation process and for a number of the important non-constraining variables. Firstly, in-sample validation aggregates the simulated microdata for comparison with the regional benchmarks used to constrain the simulation to ensure the correct spatial distribution of the primary determinants of the matching process. The proportional correlation of each constraint variable used is compared to those in the census small area population statistics. Secondly, validation of the non-constrained variable of interest in the simulated data, disposable income, is carried out by comparing SMILE county-level aggregates to county-level income statistics from the National Survey of Household Quality. Finally, a calibration procedure is used to align the disaggregated data within SMILE with known exogenous spatial distributions of disposable income and other key non-constraint variables in the SILC dataset[7]. The creation of the SMILE microsimulated dataset and the validation and calibration of the model results are fully described in Farrell et al. (2012).

All matching and value transfer techniques rely on the conditional independence assumption. Where variables in the spatial dataset are classified (X, Y) and the ones in the benefit value survey are (X, Z), meaning that we call the overlapping variables X and the non-overlapping variables Y and Z. The conditional independence assumption then states that given X, Y and Z should be independent, or equivalently, that all the correlation between Y and Z has to be explained by X. In other words the value of water quality improvements should depend only upon the values of X and not of Y. In the case of this study, as the benefit value survey was bespoke, containing a rich set of variables X that theoretically inform Z or the value to be transferred and because it was collected for the purpose of value transfer into the spatial model and thus there are relatively few Y variables, we can be satisfied that conditional independence holds.

Linking the simulated population to the WMUs and value transfer

Using a geographical information system, we overlay the 3409 EDs on to the 151 WMUs to produce a WMU identifier for each observation in the simulated population. This then allows us to link the water quality information associated with each WMU from the EPA to our simulated dataset for use in the functional value transfer. An ED

[7] The interested reader is directed to Edwards et al. (2011) for an in-depth discussion on calibration and the role of the constraint variables in the matching process and Smith et al. (2011) and Whitworth et al. (2017) for a discussion on the accuracy of microsimulation models and the impact of the choice of constraints on model outcomes.

is assigned to a WMU if more than 50% of its area is within the boundary of the WMU. Figure 1 shows the GIS link of the WMUs and the EDs and their spatial distribution. At this point the parameters from our CVM model are used to estimate the WTP to achieve GES within each WMU for every person aged 18 plus in the simulated population in each WMU. Based on the function transfer we generate average and total WTP values for each catchment that allows us to take into account the spatial heterogeneity of the target population and the water body qualities in each WMU.

Finally we compare the results from this transfer approach to the results from a primary CVM valuation exercise and a discrete choice experiment carried out in one of the catchments. This allows us to calculate transfer errors and check the transfer validity of the spatial microsimulation transfer approach.

5. Results

Summary statistics for the sample are presented in table 1. Where available the mean of the statistics are also provided for the Irish Census of Population. Despite some minor disparities, overall table 1 indicates that the sample is broadly representative of the general population of Ireland based on demographic characteristics. The only real disparity would appear to be average income where the survey sample mean is lower than average income reported by the Central Statistical Office (CSO) (CSO, 2016). The CSO figure however represents the average industrial wage for Ireland whereas respondents from the survey were asked to indicate the income bracket that best described their total personal income per year "whether from employment, pensions, state benefits, investments or any other sources". Table 1 also compares the sample and Census figures to the SMILE simulated population. As expected, given the matching constraints used, the simulated population is almost an exact match for the Census statistics for age, third level education and rural residency and also does a better job than the sample in terms of matching national average income. The distance to the nearest water body is double the size in the sample compared to the simulated population although in absolute terms this difference is still less than 1km[8].

[8] In both the sample and simulated population cases the distance is measured using GIS and is the straight line distance from the centroid of the ED that the individual is known to live in to the closest point of the nearest water body.

The results from the contingent valuation model are presented in table 2. As discussed in the methodology section a Generalized Tobit was the specification employed. Forty eight per cent of the respondents reported that they would be willing to pay something towards achieving 100% good ecological status in their water catchment. Individuals who stated they were not willing to pay because they could not afford to pay anything or that the improvements are not important to them were considered as point observations of €0. Respondents who gave other reasons for not being WTP were considered as protest bids and excluded from the analysis[9]. Of the €0 WTP responses, 189 were treated as legitimate bids while 89 were treated as protest bids. These later observations were excluded from the analysis. The total final number of responses used in the CVM analysis was therefore 764. Of these usable responses, the 189 zero WTP values were treated as uncensored observations in the estimation of the model. A further 14 WTP values were considered right censored at €200 while the remaining 561 were treated as interval observations.

The Likelihood Ratio χ^2 statistic of 67.9 shows that, taken jointly, the coefficients in the Generalized Tobit Interval model are significant at the 1% level. In relation to the estimated parameters, as expected, income and third level education were both found to have a significant and positive effect on WTP towards achieving 100% good ecological status in their water catchment. As expected, the further away an individual lives from the nearest point of the water body the less they are willing to pay towards achieving 100% good ecological status for the water body. Respondents resident in rural areas were also found to be willing to pay less than those living in urban centres. Individuals who were married and whom had visited the water body in their catchment were also more likely to have a higher WTP. The variable for having visited the water body in their catchment was only significant however at the 10% level. As mentioned in the methodology section this variable had to be simulated for the function transfer as it was not pre-existing in the SMILE population. This was done using a simple logit model to first predict whether a person in the SMILE

[9] It is standard practice in CVM analysis to ask follow-on questions of those who indicate a zero WTP for the environmental good. Based on the response to those follow-on questions, protest bidders can be identified and removed in order to avoid an underestimate of the true WTP in the population. In this case respondents who indicated that they stated €0 because they either objected to paying taxes or the government should pay or that they did not believe the work would be done to achieve the improvement were removed and the subsequent analysis performed using the remaining 764 individuals.

population is likely to have visited their local water body as a function of socio-demographic characteristics. With a pseudo R-squared of just 0.13 the explanatory power of that secondary logit is low. Even though this suggests that the spatial allocation attributable to this variable is close to random we still retain it in the CVM model and in the transfer process as it was considered theoretically important[10].

A novel feature of the CVM question was the fact that respondents were given information on the current water quality status in their own catchment area. Therefore we were able to include this measure as a covariate in our model in the form of the ratio of the % of Good quality rating to the % of poor or moderate rating for the water bodies in the catchment. The highly significant positive sign associated with this coefficient would seem to indicate that the better the water quality is at present in the catchment the more the residents of that catchment are willing to pay to bring it up to full 100% good ecological status. A similar result was found by Soliño et al. (2013) and may indicate that residents in higher water quality status catchments have a greater appreciation for the benefits that can be had from achieving 100% good ecological status in their catchment or that those who value good quality water status will have chosen to live in those higher status catchments for that very reason in the first instance.

Following the estimation of the CVM model, the coefficients from the generalised Tobit CVM model were applied to the simulated SMILE population and the resulting estimated values of WTP for each individual i in the synthetic population of each WMU are used to calculate unique average and total WTP per WMU area n ($\sum_{i=1}^{n} \hat{W}TP_{SIMi}$). An issue with any value transfer exercise is the difficultly in controlling for the differences between the policy and study sites. Using our methodology the heterogeneity in terms of the characteristics of the population in each WMU can be directly controlled for by using the simulated population which holds to Census of Population small area population constrains for household and individual numbers,

[10] We tested whether the exclusion of this variable had any influence on WTP estimation. We find that in both the CVM model and in the transfer estimation its exclusion has no statistical impact on model results or WTP estimation indicating that any measurement error risk associated with the inclusion of the constructed variable is low. Also an OLS that regressed stated WTP on the same explanatory variables, including *have visited the water body in their catchment* suggested no issue with multicollinearity, with an average variance inflation factor score of just 1.14.

age, gender and education level. Also the information on water quality standards in each WMU and the coefficient on water status in the CVM model allows us to differentiate the estimated WTP values in each WMU based on the difference in the current status between catchments.

Table 3 presents the average WTP estimates from the study and estimated for the simulated population. The estimates at the national level for average WTP per person are statistically equivalent across the sample and simulated populations. This acts as a good cross check on the transfer method. Given the higher average incomes observed in the simulated population we also test what influence this might have on WTP in the transfer process. Constraining the simulated population to have the same income distribution as the sample we find that the average WTP is reduced by €0.91 to €22.91; a difference in the simulated WTP estimate which is found to be statistically insignificant.

Figure 2 shows the average per person and total WTP per WMU area, estimated from the function transfer to the SMILE simulated population. While it is difficult to determine any distinct pattern to the average per person estimates per WMU one can make out higher values associated with the more urban WMUs (containing major population centres) and for WMUs that have high water quality status associated with them. The less developed midlands region of Ireland also displays lower per person level estimates on average. As expected the highest total WTP per WMU figures line up with the largest urban centres of Dublin, Cork, Galway city and Limerick. The more rural water management units, with lower populations, along the western sea board (particularly in parts of Donegal, Galway, Clare and Kerry) are found to display some of the lowest total WTP estimates in the country.

As a measure of the robustness of the transfer approach we were able to check our simulated estimates of WTP for the Boyne catchment to two previous primary studies that were carried out on the value of achieving GES in this particular catchment. Stithou (2011) carried out a similar CVM study for the Boyne catchment where the WTP question asked also related to the achievement of GES in the catchment. Stithou et al. (2012) also carried out a discrete choice experiment (DCE) analysis where the attributes used in the choice cards and resulting models allowed the authors to estimate the welfare impact of achieving attribute levels that were assumed to be in line with the achievement of GES in the Boyne catchment. The average WTP estimates from both these studies are shown in table 4. There is only a 5% difference between our transfer WTP estimate for the Boyne catchment and the estimate produced from the CVM study by Stithou et al. (2011) and a larger 23% difference between the Stithou et al. (2012) DCE estimates and our transfer estimate. The CVM study by Stithou et al. (2011) used the exact same model specification as employed here. Indeed the fact that we had a payment card CVM study in one of the WMUs that we could compare to was a key reason in choosing the generalized tobit specification for the transfer. Given the different methodology used in the later Stithou et al. (2012) case (the DCE) the transfer error could be still considered to be relatively low.

6. Discussion and Conclusions

In this paper we demonstrated how one might use a spatial microsimulation modelling framework in the transfer of a value function from an existing study to a policy study of interest. In our case this involved the transfer of a contingent valuation function where the value to the Irish general public of achieving GES, as specified in the WFD, was estimated as a function of the characteristics of the population and the current water quality status of the WMU in which the respondents resided. Transferring the contingent valuation function across the spatial micro simulated synthetic population within each catchment and linking, in GIS, information on the water quality status within each WMU allowed us to estimate the value of achieving GES within individual water management units across Ireland while at the same time controlling at the individual level for the heterogeneity in the population across the WMUs and for the heterogeneity in water quality status as well.

The estimated values from this function based transfer approach were then compared against the results from previous primary valuation studies that was carried out in one of the water catchment areas. The transfer errors were found to be low but particularly so when compared to the primary study in the WMU that used the same model specification as employed in this paper. Indeed transfer errors of 5% and 23% are acceptable when one considers that Brander et al. (2007) found an average transfer error equal to 186% for coral reef recreation valuation studies while, in a broader review of transfer errors in the environmental economics literature, Rosenberger and Stanley (2006) found error rates ranging between 8 and 577%.

We used a very simple CVM elicitation format in the valuation exercise. This was done as we were asking the CVM question with a transfer exercise in mind and knowing that we would be able to test the resulting estimates against a similar primary valuation study carried out in one of the WMUs. The model specification format chosen was also kept in line with the other primary study for the same reason. As demonstrated by Brouwer et al. (2008) different treatments and specification within contingent valuation studies achieve different estimation outcomes due to the elicitation format and the payment mode. Using the same function form should therefore reduce the magnitude of the transfer errors. It would also have been beneficial to include a variable in the CVM model that controlled for the respondent's general interest in environmental issues as this has been shown to affect preferences for environmental goods directly (Weible and Heikkila 2017). However no such question was asked in the survey instrument.

While the payment card version may not be the optimal elicitation format from an incentive compatibility perspective (Carson and Groves, 2007), the survey questions were designed to promote consequentiality (Vossler et al., 2012) and employing the approach does allow a 'cleaner' test of transferability based on a similar primary study in one of the WMUs. Other model specifications such as a two stage Heckman style model or a spike model, both of which could account separately for the share of zero price bidders, were alternatives that could have been employed (Ramajo-Hernández and Saz-Salazar, 2012). With these issues in mind a cautious view should be taken of the estimates generated from the chosen model although the value function does allow us to test our novel methodological approach to value transfer. We further note that Hynes et al. (2010), Bateman et al. (2011) and Czajkowski et al. (2017) have also previously used payment card based CVM models for their BT exercises.

National level spatial microsimulation models are now available across many countries that could be used for value transfer purposes. The SYNAGI (Synthetic Australian Geo-demographic Information) model in Australia (Harding et al., 2006), SimAlba in Scotland (Campbell and Ballas, 2016) and the SESIM model in Sweden (Larsson et al, 2019) being just some examples. Transferring value function to the synthetic populations generated in these models should provide a more accurate reflection of population heterogeneity at alternative spatial scales. It is possible that the researcher could simply reweight the sample to the small area census statistics within each catchment without going to the spatial microsimulation model where the variables in the census are expected to be the key explanatory variables. However if there are other variables not available in the small area statistics but that are expected to be key explanatory variables (such as income in our case) then the use of the microsimulation method may be more appropriate.

An obvious question arises as to when the researcher might be better off generating the regional weights directly for each of the respondents in the sample as was done in the spatial microsimulation transfer approach used by Hynes et al. (2010) versus transferring the sample transfer function to an existing microsimulation population as was done in this paper. We would suggest that the Hynes et al. (2010) approach is more appropriate where the sample constitutes a larger proportion of the population or when the matching variables used in the simulation process are also the key explanatory variables in the valuation function. In the Hynes et al. (2010) case the sample of farm households made up approximately 10% of the overall population of interest and the matching variables used to generate the simulated population (farm size, system and soil type) were also key explanatory variables in the CVM model. In our case our sample is approximately 1% of the overall population and the matching variables in the SMILE model are not all critical explanatory variables in the CVM model. In this case we are therefore better off relying on an existing spatial microsimulation model that has been externally calibrated to match small area population statistics and that relies on a match between a much larger sample (SILC) and the census small area population statistics.

In terms of estimating the benefit value of achieving the targets set out under the WFD, the spatial microsimulation frameworks allows the researcher to control for the concentration and non-linear distribution of populations across the WMUs and to control for the fact that the willingness to pay will vary according to an individual's geographic proximity to the water body within the catchment. Combining the synthetic microsimulated population data with environmental data such as water quality status monitoring station information using GIS has the additional potential of making even more accurate value transfers as it allows the researcher to control for differences in site quality and to control for commodity consistency. This is especially the case when, as was achieved in this study, that same information is controlled for in the value function being transferred.

References

Ballas, D., Clarke, G. P., Dorling, D. and Rossiter, D. (2007). Using SimBritain to Model the Geographical Impact of National Government Policies. Geographical Analysis 39(1), 44-77.

Bateman, I., J., Brouwer, R., Ferrini, S., Schaafsma, M., Barton, D.N., Dubgaard, A., Hasler, B., Hime, S., Liekens, I., Navrud, S., De Nocker, L., Ščeponavičiūtė, R., Semėnienė, D. (2011). Making benefit transfers work: deriving and testing principles for value transfers for similar and dissimilar sites using a case study of the non-market benefits of water quality improvements across Europe. Environmental resource Economics, 50 (3), 365–387.

Beniston, M., Stoffel, M., Harding, R., Kernan, M., Ludwig, R., Moors, E., Samuels, P., Tockner, K. (2012). Obstacles to Data Access for Research Related to Climate and Water: Implications for Science and EU Policy-Making. Environmental Science & Policy 17: 41–48.

Bergland, O., Magnussen, K., Navrud, S. (1995). Benefit Transfer: Testing for Accuracy and Reliability. Discussion Paper#D-03/1995. Department of Economics and Social Sciences, Agricultural University of Norway.

Blamey, R., Bennett, J., Morrison M. (1999). Yea-saying in contingent valuation surveys. Land Economics 75, 126-141.

Boutwell, J. and Westra, J. (2013). Benefit Transfer: A Review of Methodologies and Challenges. Resources, 2, 517-527

Boyle, K. (2003). Contingent Valuation in Practice, in Champ, P., Boyle, K., and Brown, T. A Primer on Nonmarket Valuation. Kluwer Academic Publishers.

Boyle, K., Johnson, F., McCollum, D. (1997). Anchoring and adjustment in single-bounded, contingent-valuation questions. American Journal of Agricultural Economics 79, 1495-1500

Brander, L., van Beukering, P., Cesar, H. (2007). The recreational value of coral reefs: a meta-analysis. Ecol. Econ. 63, 209–218.

Brouwer, R., Langford, I., Bateman, I., Turner, K. (2008). A meta-analysis of wetland contingent valuation studies. In: The Stated Preference Approach to Environmental Valuation III: Benefit-Cost Analysis and Natural Resource Damage Assessment. Ashgate Publishing Ltd, Aldershot

Buckley, C., Hynes, S. and Mechan, S. (2012). Supply of an ecosystem Service – Farmers' Willingness to Adopt Riparian Buffer Zones in Agricultural Catchments, Environmental Science and Policy, Vol. 24, 101-109.

Cameron, T., and D. Huppert (1989). OLS versus ML Estimation of Non-Market Resource Values with Payment Card Interval Data. Journal of Environmental Economics and Management, 17: 230-246.

Campbell, M. and Ballas, D. (2016). SimAlba: a spatial Microsimulation approach to the analysis of health inequalities. Frontiers in Public Health; 4, 10.3389/fpubh.2016.00230

Carson, R. and Groves, T. (2007). Incentive and informational properties of preference questions. Environmental Resource Economics, 37 (1), 181–210.

Clancy, D. Breen, J., Morrissey, K., O'Donoghue, C. and Thorne, F. (2012). The Location Economics of Biomass Production for Electricity Generation. In O'Donoghue, C., Ballas, D., Clarke, G. Hynes, S. and Morrissey, K. (Eds). Spatial Microsimulation for Rural Policy Analysis, Springer, London; 165–181.

CSO (2016). Earnings and Labour Costs Quarterly - Q1 2016 (Final). Central Statistics Office (CSO) Statistical Release, Dublin.

Czajkowski, M., Ahtiainen, H., Artell, J. and Meyerhoff, J. (2017). Choosing a functional form for an international benefit transfer: Evidence from a nine-country valuation experiment. Ecological Economics, 134, 104-113.

Cullinan, J., Hynes, S. and O'Donoghue, C. (2011). Using spatial microsimulation to account for demographic and spatial factors in environmental benefit transfer. Ecological Economics, 70 (4), 813-824.

Deming, W. and Stephan, F. (1940). On least square adjustment of sampled frequency tables when the expected marginal totals are known. The Annals of Mathematical Statistics, 6, 427–444.

Deville, J., Sarndal, C. and Sautory, O. (1993). Generalized raking procedures in survey sampling. Journal of the American Statistical Association, 88, 1013–1020.

Desvousges, W., M. Naughton, and Parsons, G. (1992). Benefit transfer: Conceptual problems in estimating water quality benefits using existing studies, Water Resource Research, 28(3), 675–683

D’Orazio, M., Di Zio, M. and Scanu, M. (2006). Statistical Matching. Theory and Practice. John Wiley & Sons Ltd, UK.

EPA (2015) Water Quality in Ireland 2010 – 2012, EPA publication, Wexford, Ireland.

EPA (2019) Water Quality in Ireland 2013 – 2018, EPA publication, Wexford, Ireland.

EU Environment (2015). Assessment of Member States’ progress in the implementation of Programmes of Measures during the first planning cycle of the

Water Framework Directive; Member State Report: Ireland (IE). DG Environment, Brussels.

Edwards, K. L., Clarke, G. P., Thomas, J., & Forman, D. (2011). Internal and external validation of spatial microsimulation models: Small area estimates of adult obesity. Applied Spatial Analysis and Policy, 4(4), 281-300.

Farrell N., Morrissey K. and O'Donoghue C. (2012). Creating a Spatial Microsimulation Model of the Irish Local Economy. In: Tanton R., Edwards K. (eds) Spatial Microsimulation: A Reference Guide for Users. Understanding Population Trends and Processes, vol 6. Springer, Dordrecht

Ferrini, S., M. Schaafsma, andBateman, I. (2014). Revealed and stated preference valuation and transfer: A within-sample comparison of water quality improvement values, Water Resource Research, 50 (6), 4746–4759.

Fonta, W. Ichoku, H. and Kabubo-Mariara, J. (2010). The Effect of Protest Zeros on Estimates of Willingness to Pay in Healthcare Contingent Valuation Analysis', Applied Health Economics & Health Policy, 8, 225-237

Giakoumis and Voulvoulis (2018). The Transition of EU Water Policy towards the Water FrameworkDirective's Integrated River Basin Management Paradigm. Environmental Management, 62, 819-831.

Haab, T. and McConnell, K. (2002). Valuing Environmental and Natural Resources, Cheltenham, UK: Edward Elgar.

Hasler B., Jørgensen S.L., Martinsen L., Källstrøm M., Christensen L.P., Olsen S.B., Ladenburg J., Christensen T., Dubgaard A., Levin G., Viuf, P. (2012). Valuation of the benefits of the Water Framework Directive: Danish Case Studies: Odense and Roskilde. DCE report, Aquamoney.

Iovanna, R. and Griffiths, C. (2006). Clean water, ecological benefits, and benefits transfer: A work in progress at the U.S. EPA. Ecological Economics, 60, 473 – 482.

Hanley, N. Wright, R. and Alvarez-Farizo, B. (2006a). Estimating the economic value of improvements in river ecology using choice experiments: an application to the Water Framework Directive. Journal of Environmental Management, 78: 183–93

Hanley, N., Colombo, S., Tinch, D., Black, A., Aftab, A. (2006b). Estimating the benefits of water quality improvements under the Water Framework Directive: are benefits transferable?, European Review of Agricultural Economics, 33(3): 391–413

Harding, A., Lloyd, R., Bill, A. and King, A. (2006). Assessing poverty and inequality at a detailed regional level: New advances in spatial microsimulation' in M. McGillivray and M. Clarke, (eds), Understanding Human Well-being.Helsinki, United Nations University Press, vol. pp. 239 - 261.

Hynes, S., Ghermandi, A., Norton, D. and Williams, H. (2018). Marine Recreational Ecosystem Service Value Estimation: A Meta-Analysis with Cultural Considerations Ecosystem Services 31, 410-419.

Hynes, S., Tinch, D. and Hanley, N. (2013). Valuing improvements to coastal waters using choice experiments: An application to revisions of the EU Bathing Waters Directive. Marine Policy, 40: 137–144.

Hynes, S., Hanley, N. and O'Donoghue, C. (2010). A Combinatorial Optimization Approach to Non-market Environmental Benefit Aggregation via Simulated Populations, Land Economics, 86 (2): 345–362.

Hynes, S. and Hanley, N. (2009). The ''Crex crex'' lament: Estimating landowners willingness to pay for corncrake conservation on Irish farmland, Biological Conservation 142: 180-188.

Johnson, E., Moran, D. and Vinten, A. (2008). A framework for valuing the health benefits of improved bathing water quality in the River Irvine catchment. Journal of Environmental Management, 87 (4), 633-638.

Johnston, R., Rolfe, J., Rosenberger, R. and Brouwer, R. (2015a). Introduction to benefit transfer methods. In: Johnston, R., Rolfe, J., Rosenberger, R., Brouwer, R. (2015). Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners. Springer, Dordrecht, the Netherlands.

Johnston, R. and Thomassin, P. (2010). Willingness to pay for water quality improvements in the United States and Canada: Considering possibilities for international meta-analysis and benefit transfer. Agricultural and Resource Economics Review, 39(1), 114-131.

Kolenikov, S. (2014) Calibrating survey data using iterative proportional fitting (raking). The Stata Journal, 14 (1) 22–59.

Kristofersson, D. and S. Navrud (2005). Validity tests of benefit transfer: Are we performing the wrong tests? Environmental Resource Economics, 30, 279–286.

Lehtonen, R. and Veijanen, A. (2009). Design-based methods of estimation for domains and small areas. In Rao, C. and D. Pfeffermann (Eds.), Handbook of statistics, vol. 29(B). Sample surveys: theory, methods and inference. Elsevier.

Langans, S., Reichert, P. and Schuwirt, N. (2014). The method matters: a guide for indicator aggregation in ecological assessments. Ecological Indicators, 45: 494–507.

Larsson, S., Prioux, M., Fasth, T., Ternhag, A., Struwe, J., Dohnhammar, U. and Brouwers, L. (2019). A microsimulation model projecting the health care costs for resistance to antibacterial drugs in Sweden, European Journal of Public Health, Volume 29, Issue 3, June 2019, Pages 392–396

Lovelace, R., Birkin, M., Ballas, D. and van Leeuwen, E. (2015). Evaluating the Performance of Iterative Proportional Fitting for Spatial Microsimulation: New Tests for an Established Technique. Journal of Artificial Societies and Social Simulation 18 (2) 21

Loomis, J. (1992). The evolution of a more rigorous approach to benefit transfer: benefit function transfer', Water Resources Research, 38: 701–705.

Morrison, M. and Bennett, J. (2004). Valuing New South Wales Rivers for Use in Benefit Transfer. Australian Journal of Agricultural and Resource Economics, Vol. 48, No. 4, pp. 591-611.

Morrison, M., Bennett, J., Blamey, R. and Louviere, J. (2002). Choice modelling and tests of benefit transfer. American Journal of Agricultural Economics 84: 161 – 170.
Navrud, S., Ready, R. (2007). Review of methods for value transfer. In: Navrud, S., Ready, R. (Eds.), Environmental Value Transfer: Issues and Methods. Springer, Dordrecht, 1–10.

Newbold, S., Simpson, R., Massey, D., M., Heberling, Wheeler, W., Corona, J., Hewitt, J. (2018). Benefit transfer challenges: Perspectives from U.S. practitioners. Environmental Resource Economics, 69:467–481.

Norman, P. (1999) 'Putting iterative proportional fitting on the researcher's desk.' Working Paper 99/3. School of Geography, University of Leeds, Leeds.

Norton, D., S. Hynes, E. Doherty, C. Buckley, D. Campbell, D. and Stithou, M. (2012). Using Benefit Transfer Techniques to Estimate the Value of Achieving 'Good Ecological' Status in Irish Water Bodies, Strive Report Series 94: Environmental Protection Agency.

Norton, D. and Hynes, S. (2018). Estimating the Benefits of the Marine Strategy Framework Directive in Atlantic Member States: A Spatial Value Transfer Approach, Ecological Economics, 151, 82–94.

O'Donoghue, C. (2014). Handbook of microsimulation modelling. Emerald Publishers, Bingley: Emerald.

Ramajo-Hernández, J. and Saz-Salazar, S. (2012). Estimating the non-market benefits of water quality improvement for a case study in Spain: A contingent valuation approach, Environmental Science & Policy, 22, 47-59.

Rosenberger, R., Stanley, T. (2006). Measurement, generalization, and publication: Sources of error in benefit transfers and their management. Ecological Economics, 60, 372–378.

Rosenberger, R. and Loomis, J. (2000). Using meta-analysis for benefit transfer: in-sample convergent validity tests of an outdoor recreation database. Water Resources Research, 36: 1097–107.

Rosenberger, R. and Loomis, J. (2003). Benefit transfer. In: Champ, P., Boyle, K., Brown, T. (Eds.), A Primer on Non-Market Valuation. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 445–482.

Rosenberger, R. and Johnston, R. (2009) Selection effects in meta-analysis and benefit transfer: avoiding unintended consequences. Land Economics 85: 410–428.

Rosenberger, R. and Stanley, T. (2006). Measurement, generalization, and publication: Sources of error in benefit transfers and their management. Ecological Economics, 60(2): 372–8.

Ryan, M. and Watson, V. (2009). Comparing welfare estimates from payment card contingent valuation and discrete choice experiments. Health Economics, 18, 389–401.

Smith, D., Pearce, J., & Harland, K. (2011). Can a deterministic spatial microsimulation model produce reliable small-area estimates of health behaviours? An example of smoking prevalence in New Zealand. Health & Place, 17(2), 618–624.

Schmidt, S.; Manceur, A.M.; Seppelt, R. (2016). Uncertainty of monetary valued ecosystem services—Value transfer functions for global mapping. PLoS ONE, 11, e0148524

Soliño, M., Joyce, J. and Farizo, B. (2013). Improving Water Quality in England and Wales: Local Endowments and Willingness to Pay. International Journal of Environmental Resources, 7(3):623-632.

Stithou, M., Hynes, S. and Hanley, N. (2012). Estimating the Value of Achieving 'Good Ecological Status' in the Boyne River Catchment Using Choice Experiments. Economic and Social Review, 43 (3): 24 - 37.

Whitworth, A., Carter, E., Ballas, D. and Moon, G. (2017). Estimating uncertainty in spatial microsimulation approaches to small area estimation: A new approach to solving an old problem. Computers, Environment and Urban Systems 63, 50–57.

Stithou, M. (2011). The economic value of improvements in the ecology of Irish rivers due to the Water Framework Directive. PhD Dissertation, University of Stirling.

Tanton, R. and Edwards, K. (2013). Spatial Microsimulation: A Reference Guide for Users. Springer.

Vossler, C., Doyon, M. and Rondeau, D. (2012). Truth in consequentiality: theory and field evidence on discrete choice experiments. American Economic Journal: Microeconomics, 4 (4), 145-171.

Smith, D., Pearce, J., & Harland, K. (2011). Can a deterministic spatial microsimulation model produce reliable small-area estimates of health behaviours? An example of smoking prevalence in New Zealand. Health & Place, 17(2), 618–624.

Whitworth, A., Carter, E., Ballas, D. and Moon, G. (2017). Estimating uncertainty in spatial microsimulation approaches to small area estimation: A new approach to solving an old problem. Computers, Environment and Urban Systems 63, 50–57.

Weible, C. and Heikkila, T. (2017). Understanding Positions on Hydraulic Fracturing: The Entangled Mix of Expertise, Values, and Group Affiliation. In New Strategies for Wicked Problems: Science and Solutions in the 21st Century, Corvalis: Oregon State University Press, 45–68.

Table 1. Summary Statistics for Sample, Census and Simulated SMILE Population

	Sample		Simulated Population in SMILE		2011 Census of Population
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean
Gross Income/1000	28.78	17.63	42.83	35.15	36.13*
Age	44.68	16.05	48.02	18.64	44.8
Married	0.55	0.5	0.53	0.5	0.51
Third Level	0.33	0.47	0.27	0.45	0.31
Unemployed	0.12	0.32	0.11	0.31	0.18
Foreign Nationality	0.10	0.30	0.15	0.36	0.12
Rural Resident	0.41	0.49	0.41	0.49	0.41
Have Visited Local Water Body in last 12 Months	0.44	0.5	0.49	0.5	-
Distance to Nearest Point on Water Body	1.43	1.23	0.55	1.92	-
Ratio of Good Status(%) to Poor/Moderate Status (%) in Catchment	1.46	2.47	1.18	1.67	-
Max WTP per person	17.89	35.01	-	-	-

* From CSO (2016) rather the Census

Table 2. Contingent Valuation Model Results

Variables	Coefficient	Standard Error
Gross Income/1000	0.220**	-0.08
Age	-0.087	-0.09
Married	6.160**	-2.89
Third Level	6.184**	-3.07
Unemployed	-6.860	-4.36
Foreign Nationality	-3.862	-4.33
Rural Resident	-5.104*	-2.74
Have Visited Local Water Body in last 12 Months	5.142*	-2.69
Distance to Nearest Point on Water Body	-2.370**	-1.10
Ratio of Good Status (%) to Poor/Moderate Status (%) in Catchment	1.904***	-0.54
Constant	13.610***	-5.20
Likelihood Ratio $\chi^2(10)$	68	
Log likelihood	-3253	
Observations	764	

*** Significant at 1 %; ** significant at 5 %; * significant at 10 %

Table 3. WTP results

Estimated WTP per Person	Mean	Std. Dev.
Original Study	19.87	11.74
Simulated Population	23.82	11.32

Table 4. Transfer Errors

	Average WTP for Boyne Catchment*	Transfer Error
Stitou (2011) - CVM Model	20.98 (19.32, 22.65)	-0.05
Stitou et al. (2012) - Discrete Choice Model	28.55 (8.04, 58.46)	0.23
Simulated Population Approach	22.12 (22.02, 22.19)	

* 95% confidence interval in parenthesis

Figure 1. GIS linkage of Water Management Units and Electoral Districts

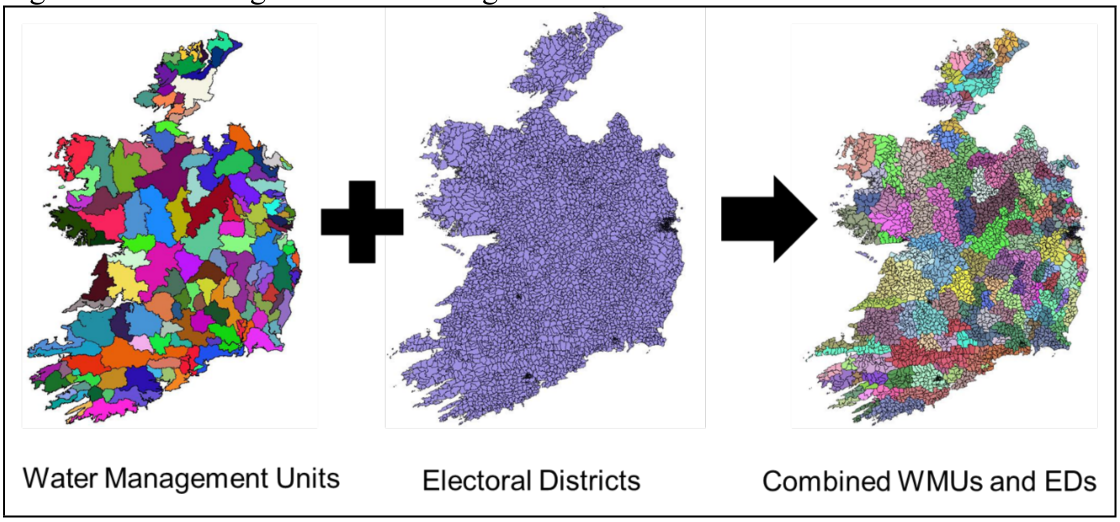
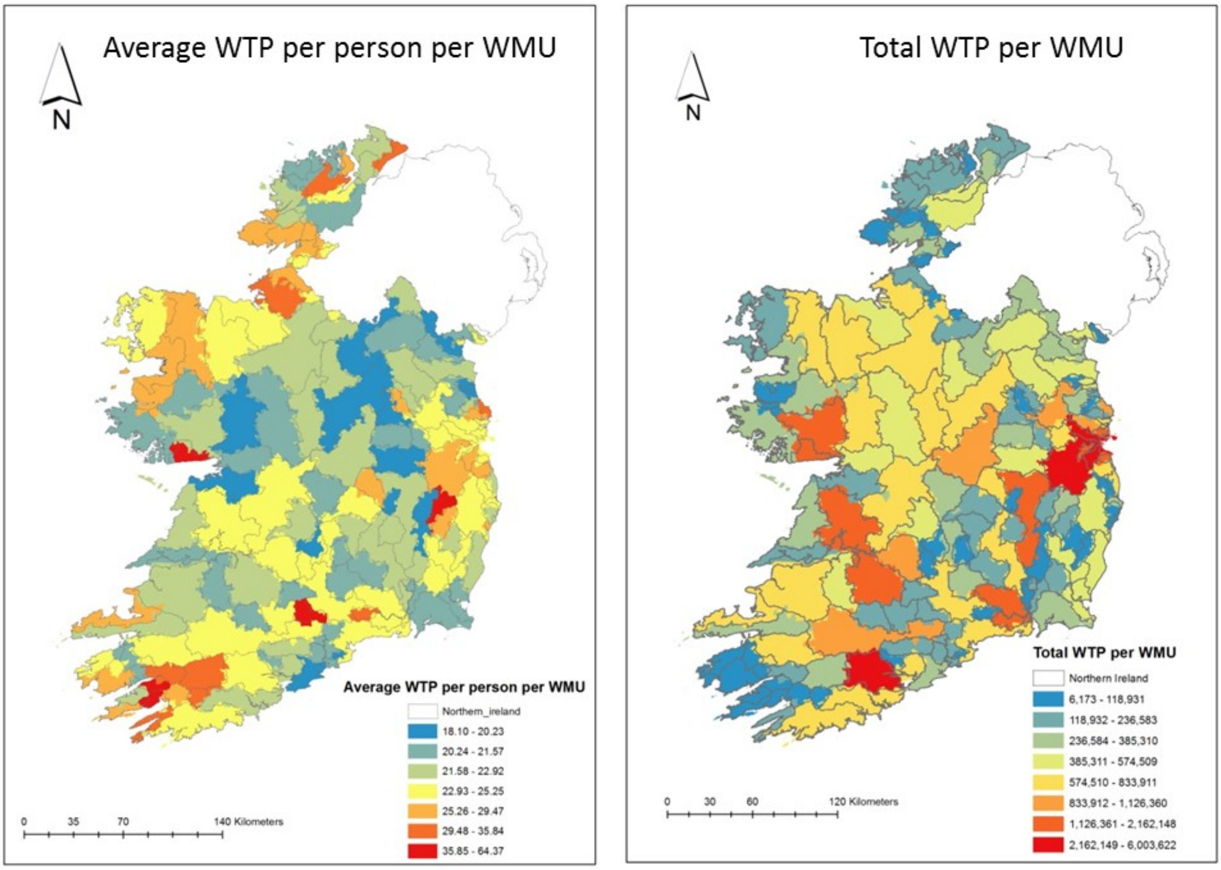


Figure 2. Average and Total WTP per WMU



Socio-Economic Marine Research Unit