Science of the Total Environment 637–638 (2018) 58–68

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Review

Valuing the visual impact of wind farms: A calculus method for synthesizing choice experiments studies

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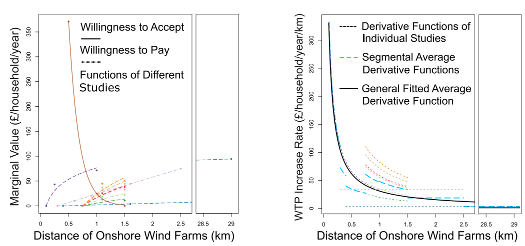
HIGHLIGHTS

- A new meta-analysis method was proposed to synthesize choice experiment studies.
- Willingness to Pay for wind farms further away followed natural logarithm curves.
- Public preferences for wind farm size and turbine height were divergent.
- Our results can be used for future spatial modelling and benefit transfer studies.
- Future meta-analysis on wind farm disamenity should include non-linear terms.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 14 February 2018
Received in revised form 24 April 2018
Accepted 30 April 2018
Available online 6 May 2018

Editor: P. Kassomenos

Keywords:
Renewable energy
Landscape impact
Stated preference
Meta-analysis
Non-linear regression

ABSTRACT

Despite the great potential of mitigating carbon emission, development of wind farms is often opposed by local communities due to the visual impact on landscape. A growing number of studies have applied nonmarket valuation methods like Choice Experiments (CE) to value the visual impact by eliciting respondents' willingness to pay (WTP) or willingness to accept (WTA) for hypothetical wind farms through survey questions. Several meta-analyses have been found in the literature to synthesize results from different valuation studies, but they have various limitations related to the use of the prevailing multivariate meta-regression analysis. In this paper, we propose a new meta-analysis method to establish general functions for the relationships between the estimated WTP or WTA and three wind farm attributes, namely the distance to residential/coastal areas, the number of turbines and turbine height. This method involves establishing WTA or WTP functions for individual studies, fitting the average derivative functions and deriving the general integral functions of WTP or WTA against wind farm attributes. Results indicate that respondents in different studies consistently showed increasing WTP for moving wind farms to greater distances, which can be fitted by non-linear (natural logarithm) functions. However, divergent preferences for the number of turbines and turbine height were found in different studies. We argue that the new analysis method proposed in this paper is an alternative to the mainstream multivariate meta-regression analysis for synthesizing CE studies and the general integral functions of WTP or WTA against wind farm attributes are useful for future spatial modelling and benefit transfer studies. We also suggest that future multivariate meta-analyses should include non-linear components in the regression functions.

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https://doi.org/10.1016/j.scitotenv.2018.04.430
0048-9697/

Contents

1. Introduction

As one of the most mature renewable energy technologies, wind energy has developed rapidly around the world (GWEC, 2017; Leung and Yang, 2012). In the UK, for example, the onshore wind installed capacity has tripled between 2009 and 2016 while offshore wind installed capacity has increased by six times (BEIS, 2017). Despite the great potential to mitigate carbon emission and air pollution, onshore and offshore wind farms could also cause negative environmental impacts such as noise, wildlife loss and visual disamenity (Dai et al., 2015; Saidur et al., 2011). Although wind energy is generally supported by the public, construction of new wind farms is often confronted with opposition from local communities (Bell et al., 2005; Bell et al., 2013). Studies have been devoted to understanding the public perception and acceptance of wind farms and the underlying determinants (Fast, 2013; Thayer and Freeman, 1987; van der Horst, 2007; van der Horst and Toke, 2010; Warren et al., 2005; Warren and McFadyen, 2010; Wolsink, 2000). The visual impact on landscapes has been identified as one of the most important determinants of local opposition to wind farms (Johansson and Laike, 2007; Pasqualetti, 2011; Wolsink, 2007).

From the economic view, visual impact is an environmental externality which is difficult to be valued in the current market. To help policy makers and planning authorities to take better account of visual impact when assessing the costs and benefits of wind farms, a growing number of non-market valuation studies have been conducted to estimate the monetary value of the visual impact of wind farms using the methods of Hedonic Pricing (Gibbons, 2015; Heintzelman and Tuttle, 2012; Hoen et al., 2011; Lang et al., 2014; Sims et al., 2008; Sunak and Madlener, 2016), Contingent Valuation (Bigerna and Polinori, 2015; du Preez et al., 2012; Groothuis et al., 2008; McCartney, 2006; Mirasgedis et al., 2014; Riddington et al., 2010) and Choice Experiment (Alvarez-Farizo and Hanley, 2002; Aravena et al., 2006; Ek and Matti, 2015; García et al., 2016; Strazzera et al., 2012). Hedonic Pricing studies reveal the implicit value of visual impact by investigating the relationship between house prices and the proximity to wind farms. As Knapp and Ladenburg (2015) summarized, results from the literature were mixed in terms of whether wind farms exhibited significantly negative effects on nearby house prices.

Contingent Valuation and Choice Experiment (CE) studies use survey questions to construct hypothetical markets for eliciting participants' willingness to pay (WTP) or willingness to accept (WTA) compensation for the landscape/scenery change due to wind farms. While the former makes relatively simple, direct estimation for a single wind farm project, CE studies describe multiple wind farms as different combinations of defined attributes at different levels (e.g. distance from the wind farm to residential areas, the number of turbines in the wind farm) and ask participants to state their preferences for different wind farms through a rigorously designed recursive procedure. By setting one of the wind farm attributes to be monetary values (e.g. surcharge or discount of household electricity bills), CE studies can estimate the marginal values (WTP or WTA) of non-monetary attributes, i.e. how much participants are willing to accept or pay for specified change in the attributes (marginal WTP and WTA are simply referred to as WTP and WTA hereafter).

With the growing number of non-market valuation studies on wind farm externalities, several reviews and meta-analyses have been found in the literature. Strazzera et al. (2012), Ladenburg and Lutzeyer (2012) and Knapp and Ladenburg (2015) tabulated valuation results from different studies and provided narrative reviews, while Mirasgedis et al. (2014), Bigerna and Polinori (2015) and Mattmann et al. (2016) applied multi-variate meta-regression analysis to identify explanatory variables for the variation among different valuation results. These reviews and meta-analyses have provided useful insights, for example, that offshore wind farms are generally preferred than onshore wind farms (Mattmann et al., 2016; Mirasgedis et al., 2014) and WTA estimates are statistically larger than WTP estimates (Bigerna and Polinori, 2015; Mirasgedis et al., 2014). Furthermore, people significantly prefer locating wind farms further away from housing (Bigerna and Polinori, 2015; Mirasgedis et al., 2014), but there is a distance decay effect, i.e. the marginal benefit of moving wind farms away decreases with distance (Knapp and Ladenburg, 2015; Ladenburg and Lutzeyer, 2012).

Notwithstanding the useful insights, those reviews and meta-analyses have limitations. For instance, Mirasgedis et al. (2014) and Bigerna and Polinori (2015) did not include two important wind farm attributes that are closely related to the level of visual impact, i.e. the number of turbines in the wind farm and the height of turbines.

Bigerna and Polinori (2015) only considered onshore wind farms. Mattmann et al. (2016) excluded all WTA studies and six CE studies from their analysis and did not take account of turbine height as well as the distance from wind farms to residential areas in the regression. From the methodological point of view, the omission of certain wind farm attributes can be largely attributed to the use of the mainstream multi-variate regression technique because attributes like turbine height have been used by relatively few studies, thus adding them into the regression would substantially reduce the sample size of the meta-analysis.

This paper proposes a new meta-analysis method of synthesizing the results of CE studies and applies this method to the literature on visual impact of wind farms. Unlike the multi-variate meta-regression, this new method performs separate analysis on individual wind farm attributes, i.e. the distance from the wind farm to residential/coastal areas, the size of wind farm (namely the number of wind turbines) and turbine height. This new analysis method involves 1) deriving the WTP or WTA functions for each of the three attributes from individual valuation studies, 2) calculating the average derivatives of the WTP or WTA functions from different studies for each attribute range that has been evaluated by different numbers of studies, 3) fitting the average derivative function across the whole evaluated attribute range, and lastly 4) integrating the fitted average derivative function to derive a general integral function which describes the general relationship between the attribute and estimated WTP or WTA across all studies. Due to the procedures of deriving the derivative and integral functions, we call this new analysis method a “calculus method”.

2. Method

2.1. Literature retrieval and selection

To collate monetary valuation results of the visual impact of wind farms, peer-reviewed papers were retrieved from Web of Science in Feb. 2017, using all combinations of three groups of search terms which described the valuation methods, the visual impact and disamenities, and wind energy or renewable energy in general (Table 1). In the search syntax, the three groups of search terms were combined with “AND”, while within each group, multiple search terms were combined with “OR”.

A total of 232 papers were retrieved. Titles and abstracts were screened to identify the relevant papers for full-text review. Additional relevant literature (including both peer-reviewed studies and grey literature) which were found during the review process (e.g. cited by the reviewed papers) were also examined. We selected CE studies that estimated the marginal values of at least one of the three attributes, namely distance, the number of turbines and turbine height. Contingent Valuation studies were excluded as they did not provide value estimation for specific attributes of wind farms. Several CE studies which focused on the visual impact of wind farms but did not provide comparable marginal values of the three attributes were also excluded from this meta-analysis (Fooks et al., 2017; Landry et al., 2012; Lutzeyer et al., 2016).

Table 1
Search terms for literature retrieval.

Group	Search terms
Method	Willingness to pay, WTP, willingness to accept, WTA, stated preference(s), choice model(s), contingent valuation, choice experiment(s)
Disamenities	Externality(-ies), disamenity(-ies), amenity(-ies), visual, landscape(s), view(s), scenic, aesthetic(s)
Type of energy	Renewable(s), wind

2.2. Data collection and treatment

We used several procedures to convert the original valuation results in the reviewed literature into comparable monetary values. In cases where multiple choice models were applied, the average estimates of multinomial logit models and random parameters logit models were adopted for simplicity. Results of different survey areas in the same paper were processed separately. All monetary estimates were converted into yearly household payments for consistency and then inflated to values in Feb. 2017 by taking account of the Consumer Price Index (CPI) inflation in different countries. The “inflated” values were calculated using online CPI inflation calculators provided by official departments/institutes (e.g. Bank of England, United States Department of Labor) or specialized websites (Fxtop.com and StatBureau.org) when no official calculators were available. Lastly, all inflation-adjusted values in different currencies were converted to British Pounds with the exchange rates in Feb. 2017 (e.g. €1 = £0.88).

2.3. Function fitting for individual studies

Three attributes of wind farms, namely the distance from wind farms to residential (onshore wind farms) or coastal (offshore wind farms) areas, the size of wind farms in terms of the number of wind turbines and turbine height, were chosen for analysis in this study because they were the most used attributes to indicate the level of visual impact and the numeric nature of these attributes made it suitable for mathematical function deduction. For each study, a function was established to describe the relationship between the WTP or WTA and each attribute.

For studies where the effect of the attributes on WTP or WTA was estimated in the linear form (e.g. £/household/year/km), simple linear functions were established:

$$y = a * (x-b), \text{ or } y = a * (b-x) \tag{1}$$

where y is the WTP or WTA, x is the attribute, a is the estimated slope and b is the base-level of the attribute where the WTP or WTA is assumed to be zero. In cases where the attributes were treated as categorical variables with multiple levels, but only two levels showed significant difference in the WTP or WTA, similar linear functions were established between the two levels.

For studies where the attributes were treated as categorical variables and significant differences were found between multiple attribute levels, if linear functions could not provide a good fit, non-linear regression was applied using the statistical software R (R-Core-Team, 2016) to fit the WTP or WTA against the attributes. After comparing the model fit of multiple potential functions (e.g. with or without a constant term), two non-linear functions were chosen for describing the increasing and decreasing trend of WTP or WTA, respectively:

$$y = a * \ln(x/b) \tag{2}$$

where a is the estimated coefficient and b is the base-level of the attribute where the WTP or WTA is assumed to be zero;

$$y = a/\exp(b * x) \tag{3}$$

where both a and b are estimated coefficients.

Model fitting was assessed by two means, namely the p-value of the estimated coefficients and the pseudo $R^2 = 1 - SSE/SST$, where SSE is the sum of squared error and SST is total sum of squares. Other function forms, such as $y = a * \ln(x/b) + c * x$, were also examined but not adopted due to the poor performance in model fitting (e.g. with insignificant coefficients $p > 0.05$).

2.4. Average derivative fitted functions and general integral functions

Being marginal values, the functions of WTP or WTA against attributes in each study applied to certain range of the attributes where the WTP or WTA at the starting points were assumed to be zero. In other words, these WTP or WTA estimates are the difference between different attribute levels instead of absolute values. Therefore, it is not appropriate to directly use the estimated WTP or WTA and the corresponding attribute levels to derive a general function to synthesize the results from different studies. Here we propose a "calculus method" which is based on averaging the derivatives of WTP or WTA functions of individual studies and deriving a general form by integration.

Take the distance of onshore wind farms as an example, ten WTP studies were found to evaluate different distance ranges between 0.1 km and 29 km (Table 2 and Fig. 1). The overlaps of the evaluated distance ranges of different studies divided the whole distance range (0.1 km–29 km) into seven segments which were evaluated by different numbers of studies: Segments 1 (0.1 km–0.3 km) and 7 (2.5 km–29 km) were only evaluated by a single study; Segment 2 (0.3 km–0.4 km) and Segment 6 (1.5 km–2.5 km) were evaluated by two studies; Segment 3 (0.4 km–0.75 km) was evaluated by three studies; Segment 5 (1.0 km–1.5 km) by nine, and Segment 4 (0.75 km–1.0 km) by ten studies. After establishing the function of WTP against distance for each of the ten studies (Table 2), we derived the average d(WTP)/d(distance) for each of the seven segments. For example, the average derivative function of Segment 2 was (33.25/distance + 34.10)/2, where 33.25/distance came from Vecchiato (2014) and 34.10 was the derivative (linear slope) of Oehlmann and Meyerhoff (2017). For each segment, we then calculated the average d(WTP)/d(distance) for ten equal-spaced points (for the attribute of wind farm size, the minimum interval was 1 turbine). We used all these points ($7 \times 10 = 70$ points in this example) to fit an overall function for d(WTP)/d(distance) along the whole distance range (0.1 km–29 km) with non-linear regression (Fig. 5). Lastly, by integrating this average derivative fitted function, we derived a general integral function that described the overall relationship between WTP and distance across all the ten studies.

For other wind farm attributes, if the WTP or WTA functions in different studies were all linear against the attributes (which means that the derivatives of these functions were all constants), the weighted average derivatives were calculated based on the attribute ranges those WTP or WTA functions applied to (Figs. S1–S3).

3. Results

A total of 17 CE studies that estimated the marginal values of at least one of the three wind farm attributes (distance, the number of turbines and turbine height) were analysed in this study (Table S1 in the supplementary materials). Among these 17 CE papers, eight of them evaluated onshore wind farms, four evaluated offshore studies, two evaluated wind farms in general and three evaluated wind farms together with other energy sources. The earliest CE survey we found on the visual impact of wind farms was conducted in 2002 (Ek, 2006) while the latest was in 2015 (García et al., 2016). Nearly all the CE studies (16 out of 17) were conducted in Europe, with one study in the USA. There were nine studies at the local-scale and eight studies at the national level. Five studies were conducted via telephone interviews, four via personal (face-to-face) interviews and online surveys respectively, three via mail surveys and one survey was self-completed by the respondents (after distributing the questionnaires in person). The sample sizes of these studies ranged from 114 (face-to-face interview) to 3213 (online survey). Based on the classifications of visualisation proposed by Hevia Koch and Ladenburg (2016), nine studies did not use any visualisation to demonstrate the different levels of wind farm attributes to respondents in the surveys, two studies used simple unscaled photo/pictograms, one study used relative-size visualisation, three studies used generic scaled visualisation (photos with simulated turbines) and two studies used site-specific scaled visualisation.

3.1. Estimated marginal values and functions of individual studies

3.1.1. Marginal values of onshore wind farm distance

Table 2 lists 11 studies (results of surveys in different regions/years but reported in one paper were considered separately) which estimated the marginal values of moving onshore wind farms to different distances and the fitted WTP or WTA functions for individual studies. Only one study adopted WTA as the welfare measure (Brennan and Van Rensburg, 2016). Most studies focused on the distance range of 0.1 km–2.5 km, except Fimereli and Mourato (2013) which investigated wind energy together with biomass and nuclear power in the UK considered distance up to 29 km. In general, respondents preferred wind farms located at greater distances as their WTP increased with distance and their WTA decreased with it (Fig. 1).

For the two studies that estimated the linear distance effect on WTP, respondents' WTP increased with the distance at the rate of £3.3/household/year/km within the rage of 0.4 km–29 km (Fimereli and Mourato, 2013) and £34/household/year/km within the range of 0.3 km–2.5 km (Oehlmann and Meyerhoff, 2017). The difference might be partly due to the markedly different distance ranges evaluated by the two studies.

For studies which estimated the distance effect on WTP as non-linear, the relationship between WTP and distance can be fitted by Function (2). A series of studies conducted in Germany focused on the distance range of 0.75 km–1.5 km (i.e. $b = 0.75$), their estimated coefficient a ranged from 19.75 to 82.62 (Drechsler et al., 2011; Liebe et al., 2012; Mariel et al., 2015; Meyerhoff, 2013; Meyerhoff et al., 2010). In another study in Italy which focused on the distance range of 0.1 km–1.0 km (i.e. $b = 0.1$) the estimated coefficient a was 33.25 (Vecchiato, 2014).

As for the only study using WTA as the welfare measure, the relationship between respondents' WTA and distance followed an reciprocal exponential function: $y = 5555/\exp.(5.41 * x)$, within the distance range of 0.5 km–1.5 km (Brennan and Van Rensburg, 2016).

3.1.2. Marginal values of offshore wind farm distance

Four studies were found to estimate the marginal values of moving offshore wind farms to different distances, which all used WTP as the welfare measure (Table 3) and evaluated a much larger distance range (1.5 km–50 km) compared with studies on onshore wind farms. Ladenburg and Dubgaard (2007, 2009) found that Danish respondents' WTP for offshore wind farms increased with distance and can be fitted by the function of $y = 81.7 * \ln(x/8)$ within the range of 8 km–50 km. Similar logarithm relationship between WTP and distance was also found by Krueger et al. (2011) in Delaware of the USA, while the estimated coefficient a was 7.7, 13.6 and 24.1 for inland, bay and ocean (island) residents respectively within the distance range of 1.5 km–32.2 km (Fig. 2). In another study conducted in Denmark, Ladenburg et al. (2011) found an average linear increase rate of WTP with distance as 0.84 £/household/year/km between 8 km and 50 km.

Westerberg et al. (2013) estimated tourists' WTP for avoiding wind farms at 5, 8 and 12 km off the Languedoc Rousillon coast in France. Three latent classes of respondents showed different patterns of increasing WTP for locating offshore wind farms at greater distance. Due to the use of different payment vehicle (weekly accommodation fee), these results were difficult to compare with results of other studies and thus were not included in further analyses.

3.1.3. Marginal values of wind farm size (the number of wind turbines)

Table 4 lists 12 studies which estimated the marginal values of wind farm size. Most studies focused on the size of 2–50 turbines, except Navrud and Braten (2007) which took account of large wind farms with up to 100 turbines. Respondents in four studies did not show significant preference for either smaller or larger wind farms, thus no

Table 2
Marginal values of moving onshore wind farms to different distances.

Study	Welfare measure	Marginal values (£/household/year)	Function	Model fitting
Meyerhoff et al. (2010)_City1[a]	WTP	0.75 → 1.1 km: 36.8 0.75 → 1.5 km: 44.1	$y = 71.22 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.05$ $R^2 = 0.89$
Drechsler et al. (2011)	WTP	0.75 → 1.1 km: 36.8 0.75 → 1.5 km: 44.9	$y = 72.10 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.05$ $R^2 = 0.90$
Meyerhoff (2013)	WTP	0.75 → 1.1 km: n.s./n.s./26.0[b] 0.75 → 1.5 km: n.s./n.s./38.4	Latent Class 3: $y = 58.32 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.01$ $R^2 = 0.98$
Meyerhoff et al. (2010)_City2[a]	WTP	0.75 → 1.1 km: 44.8 0.75 → 1.5 km: 50.0	$y = 82.62 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.05$ $R^2 = 0.85$
Liebe et al. (2012)_test[c]	WTP	0.75 → 1.1 km: 18.3 0.75 → 1.5 km: 22.0	$y = 35.49 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.05$ $R^2 = 0.90$
Liebe et al. (2012)_retest[c]	WTP	0.75 → 1.1 km: 12.4 0.75 → 1.5 km: 10.8	$y = 19.75 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.10$ $R^2 = 0.62$
Mariel et al. (2015)	WTP	0.75 → 1.1 km: n.s./n.s./31.5[b] 0.75 → 1.5 km: n.s./n.s./33.0	Latent Class 3: $y = 55.71 * \ln(x/0.75)$ $(0.75 \le x \le 1.5$ km)	$P < 0.05$ $R^2 = 0.81$
Vecchiato (2014)[d]	WTP	0.1 → 0.25 km: 43.2 0.1 → 1.0 km: 71.5	$y = 33.25 * \ln(x/0.1)$ $(0.1 \le x \le 1.0$ km)	$P < 0.05$ $R^2 = 0.93$
Fimereli and Mourato (2013)	WTP	3.3 per km	$y = 3.30 * (x-0.4)$ $(0.4 \le x \le 29$ km)	N.A. [e]
Oehlmann and Meyerhoff (2017)[f]	WTP	34.1 per km	$y = 34.10 * (x-0.3)$ $(0.3 \le x \le 2.5$ km)	N.A.
Brennan and Van Rensburg (2016)	WTA	0.5 → 1.0 km: −346 0.5 → 1.5 km: −371	$y = 5555/\exp.(5.41 * x)$ $(0.5 \le x \le 1.5$ km)	$P < 0.05$ $R^2 = 0.99$

[a] Meyerhoff et al. (2010) conducted two surveys in two German cities and estimated WTP separately.
[b] Results of three latent classes of respondents; "n.s." means not significant.
[c] Liebe et al. (2012) conducted a test/retest study in 2008 and 2009 separately.
[d] Although this study did not specify onshore or offshore wind farms, it was assumed to focus on onshore wind farms given the distance.
[e] There is no model fitting information here as the function was directly established with the estimated slope and the base-level distance in the original study.
[f] The result presented here is the average of the estimates of four subsamples differed in the information given before the choice experiment.

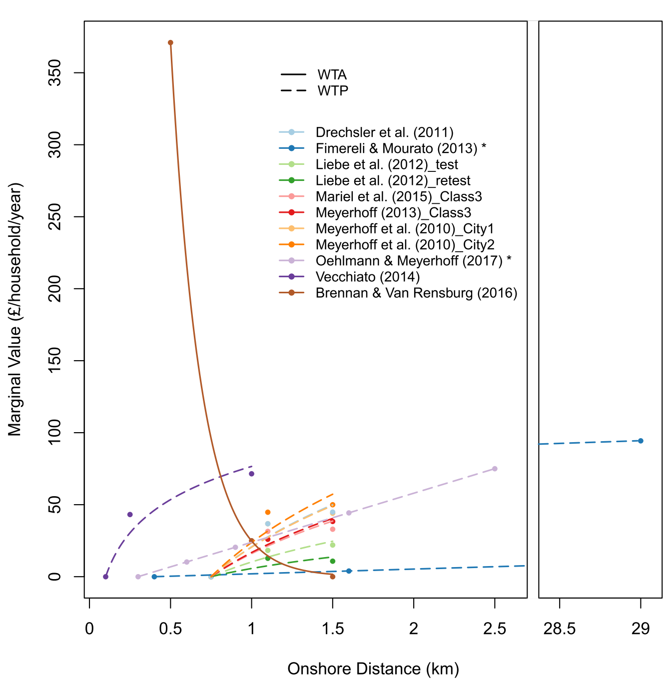

Fig. 1. Estimated marginal values (points) and fitted functions (curves/lines) of moving onshore wind farm to different distances. *Studies that evaluated wind energy together with other renewable energy. Points indicate the original estimated marginal values (WTP or WTA) at different distance levels, curves/lines indicate the fitted WTP or WTA functions of individual studies. For example, Vecchiato (2014) (in purple) found that respondents were willing to pay £43.2 and £71.5/household/year for moving wind turbines from 0.1 km to 0.25 km and 1.0 km, respectively. The WTP function derived from these three distance levels was $y = 33.25 * \ln(x/0.1)$, setting the marginal WTP at 0.1 km as zero.

significant estimates were obtained (Drechsler et al., 2011; Ladenburg and Dubgaard, 2007; Liebe et al., 2012; Meyerhoff et al., 2010). In the other studies, respondents showed divergent preferences for the size of wind farms (Fig. 3).

Three studies using WTA as the welfare measure all found that respondents preferred smaller wind farms with fewer turbines and the compensation they required for the disamenity of windfarm increased with the number of turbines at the rate of £12.0, £32.4 and £10.88/household/year/turbine, respectively (Brennan and Van Rensburg, 2016; Dimitropoulos and Kontoleon, 2009; García et al., 2016). Similar preferences for smaller wind farms were also found among respondents in Oehlmann and Meyerhoff (2017) and respondents in the latent Class 3 of Meyerhoff (2013) and Mariel et al. (2015). However, other latent classes of respondents in Meyerhoff (2013) and Mariel et al. (2015) as well as respondents in Navrud and Braten (2007) and Vecchiato (2014) showed the opposite preference for larger wind farms with more turbines.

Navrud and Braten (2007) was the only study where the WTP against wind farm size fitted a non-linear function, $y = 23.65 * \ln(x/7)$, within the range of 7–100 turbines. For WTP studies that estimated the linear effect of wind farm size, the positive effect ranged from £0.27 to £0.93/household/year/turbine while the negative effect ranged from £-1.34 to £-1.56/household/year/turbine. It can be noticed that the size effect on WTP was considerably smaller than the effect on WTA, which is consistent with findings in previous literature (Bigerna and Polinori, 2015; Mirasgedis et al., 2014).

3.1.4. Marginal values of turbine height

Turbine height is another commonly used attribute to indicate the level of visual impact of wind turbines. As shown in Table 5, nine studies were found to estimate the marginal values of turbine height, but significant estimates were only obtained by five of them, which focused on

Table 3
Marginal values of moving offshore wind farms to different distances.

Study	Welfare measure	Marginal value (£/household/year)	Function	Model fitting
Ladenburg and Dubgaard (2007, 2009)	WTP	8 → 12 km: 49.2 8 → 18 km: 103 8 → 50 km: 130	$y = 81.74 * \ln(x/8)$ $(8 \le x \le 50$ km)	$P < 0.01$ $R^2 = 0.80$
Ladenburg et al. (2011)	WTP	0.84 per km[a]	$y = 0.84 * (x - 8)$ $(8 \le x \le 50$ km)	N.A.
Krueger et al. (2011)	WTP	1.45 → 32.2 km: 19.4/35.3/82.1[b] 5.79 → 32.2 km: 9.0/11.5/70.6 9.66 → 32.2 km: 0.8/6.0/36.0 14.5 → 32.2 km: 0/2.1/27.3	Inland: $y = 7.67 * \ln(x/1.5)$ $(1.45 \le x \le 32.2$ km) Bay: $y = 13.62 * \ln(x/1.5)$ $(1.45 \le x \le 32.2$ km) Ocean (Island): $y = 24.05 * \ln(x/1.5)$ $(1.45 \le x \le 32.2$ km)	Inland: $P < 0.001$ $R^2 = 0.86$ Bay: $P < 0.001$ $R^2 = 0.89$ Ocean: $P < 0.001$ $R^2 = 0.88$
Westerberg et al. (2013)	WTP	No wind farm → wind farm at 5 km: −27.9/−37.0/−252[c] Wind farm at 8 km: 23.0/−19.3/−136 Wind farm at 12 km: n.s./40.7/−37.2 (£/tourist/week)	Class 1: $y = 16.97 * x - 113$ $(5 \le x \le 8$ km) Class 2: $y = \exp(0.37 * x) - 41$ $(5 \le x \le 12$ km) Class 3: $y = 245 * \ln(x) - 647$ $(5 \le x \le 12$ km)	Class 1: N.A. Class 2: $P < 0.05$ $R^2 = 0.99$ Class 3: $P < 0.01$ $R^2 = 0.99$

[a] The average results of the sample with cheap-talk treatment and the sample without it.
[b] Results of inland, bay and ocean (island) residents, respectively. The original estimates in the paper were external costs of locating turbines at difference distances, i.e. the WTP at 32.2 km minus WTP at other distance levels. The results presented here were calculated from the original estimates which assumed the WTP for locating wind turbines at 1.5 km as 0.
[c] Results of three latent classes of respondents, negative values mean discount in accommodation fees while positive values mean surcharge.

onshore wind turbines at the height of 50 m–200 m. Similar with the case of wind farm size, respondents also showed divergent preferences for turbine height (Fig. 4).

Two WTA studies both found that respondents preferred smaller turbines as they required more compensation for higher (larger) turbines (Fig. 4). While respondents' WTA increased at the rate of £7.92/household/year/me between 75 m and 135 m in Dimitropoulos and Kontoleon (2009), the relationship between WTA and turbine height followed the non-liner function of $y = 258 * \ln(x/80)$ between 80 m and 180 m in Brennan and Van Rensburg (2016). Respondents in one of the WTP studies, Vecchiato (2014), also preferred smaller turbines as their WTP decreased with turbine height at the rate of £-0.39/household/year/m between 50 m to 200 m. However, respondents in the retest survey of Liebe et al. (2012) and the latent Class 1 of Meyerhoff (2013) showed the opposite preference for higher (larger) turbines and their WTP increased at the rate of £0.11 and £0.28/household/year/m respectively between 110 m and 200 m.

Again, both negative and positive effects of turbine height on WTP were much smaller than the effect on WTA. In addition to the difference inherent to the use of different welfare measures, the substantial difference between the WTP and WTA estimates might also be attributed to the fact that the upper-bound payment levels in the two WTA studies were £300 and £550/household/year respectively, while the highest payment level in the WTP studies was only £138/household/year.

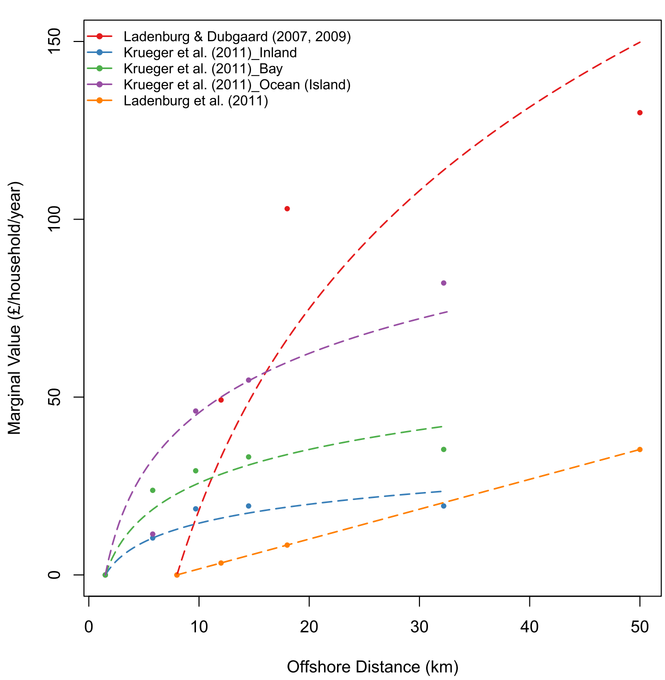

Fig. 2. Estimated WTP (points) and fitted functions (curves/lines) of moving offshore wind farms to different distances.

3.2. Average derivative fitted functions and general integral functions

As explained in Section 2.4, after establishing the WTP or WTA functions for individual studies, the derivatives of those WTP or WTA functions were used to fit the average derivative functions and then derive the general integral functions to describe the overall relationship between WTP or WTA and wind farm attributes across different studies. Since divergent preferences were found for the size of wind farm and turbine height, separate functions were derived for the two groups of respondents with divergent preference.

3.2.1. Distance of onshore wind farms

Based on the derivatives of WTP-distance functions of ten individual studies, the average derivative fitted function of WTP against onshore wind farm distance is:

$$y = 30.94/x \tag{4}$$

where y is d(WTP)/d(distance) (£/household/year/km), x is distance ($0.1 \le x \le 29$ km). The coefficient estimation is significant at the 0.001 level and the pseudo R^2 of the model fitting is 0.93 (Fig. 5). Based on Function (4), the general integral function that synthesized the

Table 4
Marginal values of wind farm size (number of wind turbines).

Study	Welfare measure	Marginal value (£/household/year)	Function	Model fitting
Dimitropoulos and Kontoleon (2009)	WTA	32.4 per turbine	$y = 32.4 * (x - 2)$ ($2 \le x \le 40$ turbines)	N.A.[a]
Brennan and Van Rensburg (2016)	WTA	12.0 per turbine	$y = 12.0 * (x - 8)$ ($8 \le x \le 40$ turbines)	N.A.
García et al. (2016)	WTA	10.88 per turbine	$y = 12.0 * (x - 9)$ ($9 \le x \le 18$ turbines)	N.A.
Meyerhoff et al. (2010)	WTP	n.s.		
Drechsler et al. (2011)	WTP	n.s.		
Liebe et al. (2012)	WTP	n.s.		
Meyerhoff (2013)	WTP	16–18 → 10–12 turbines: n.s. 16–18 → 4–6 turbines: n.s. (n.s./−8.6/18.7)[b]	Class2: $y = 0.61 * (x - 4)$ Class3: $y = 1.34 * (18 - x)$ ($4 \le x \le 18$ turbines)	N.A. [c]
Mariel et al. (2015)	WTP	16–18 → 10–12 turbines: n.s. 16–18 → 4–6 turbines: n.s. (−13.0/n.s./21.8)[c]	Class1: $y = 0.93 * (x - 4)$ Class3: $y = 1.56 * (18 - x)$ ($4 \le x \le 18$ turbines)	N.A.
Oehlmann and Meyerhoff (2017)	WTP	18–25 → 5–10 turbines: 28.9 18–25 → 35–50 turbines: −32.8	$y = -1.37 * x + 68$ ($5 \le x \le 50$ turbines)	$P < 0.05$ $R^2 = 0.99$
Vecchiato (2014)	WTP	50 → 15 turbines: n.s. 50 → 4 turbines: −12.3[d]	$y = 0.27 * (x - 4)$ ($4 \le x \le 50$ turbines)	N.A.
Ladenburg and Dubgaard (2007)	WTP	n.s.		
Navrud and Braten (2007)	WTP	100 → 20 turbines: −49.4 100 → 7 turbines: −66.1	$y = 23.65 * \ln(x/7)$ ($7 \le x \le 100$ turbines)	$P < 0.01$ $R^2 = 0.97$

[a] There is no model fitting indicator here as the function was directly established with the estimated slope and the base-level distance from the original study.
[b] Estimate for the whole sample was not significant due to conflicting preferences of different latent classes of respondents.
[c] There is no model fitting indicator as the functions were fitted for two data points only.
[d] This estimate was only significant at the 90% level.

relationships between WTP and the distance of onshore wind farms across the ten studies is:

$$y = 30.94 * \ln(x) + C \quad (5)$$

where y is WTP (£/household/year), x is distance ($0.1 \le x \le 29$ km) and C is the constant depending on the base-level of distance where the WTP is set to be zero.

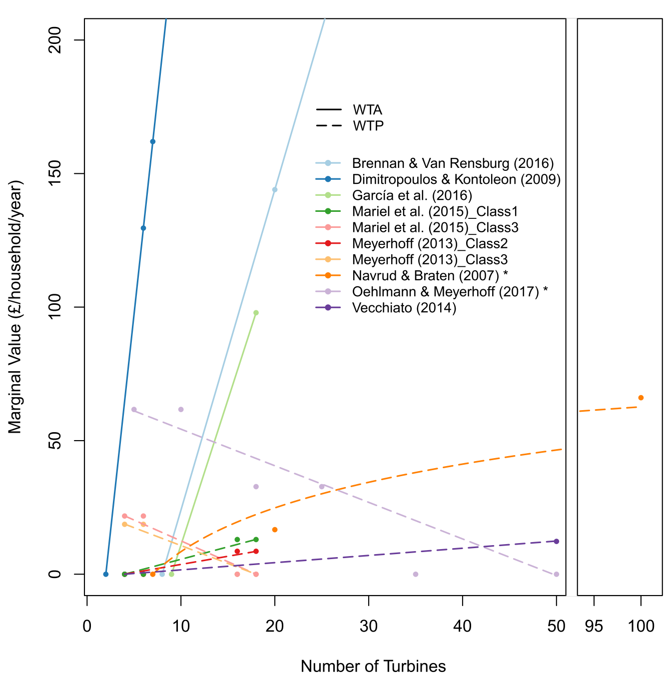

Fig. 3. Estimated marginal values (points) and fitted functions (curves/lines) of the size of wind farms. *Studies that evaluated wind energy together with other renewable energy.

Since there was only one study that investigated respondents' WTA for onshore wind farm Brennan and Van Rensburg (2016), no average derivative functions and general integral function were derived.

3.2.2. Distance of offshore wind farms

Estimates from Ladenburg and Dubgaard (2007, 2009), Krueger et al. (2011) and Ladenburg et al. (2011) were used to derive the average derivative fitted function of WTP against the distance of offshore wind farms:

$$y = 12.90/x + 0.88 \quad (6)$$

where y is $d(\text{WTP})/d(\text{distance})$ (£/household/year/km) and x is distance ($1.5 \le x \le 50$ km). The coefficient estimation is significant at the 0.001 level and the pseudo R^2 of the model fitting is 0.96 (Fig. 6). Accordingly, the general integral function is:

$y = 12.90 * \ln(x) + 0.88 * x + C$ (7)where y is WTP (£/household/year), x is distance ($1.5 \le x \le 50$ km) and C is the constant depending on the base-level of distance where the WTP is set to be zero.

3.2.3. Size of wind farm (the number of turbines)

As reported in Section 3.1.3, respondents showed divergent preferences for the size of wind farms. For those who preferred smaller wind farms, their WTA increased with the number of wind turbines at the weighted average derivative (rate) of £22.92/household/year/turbine within the range of 2–40 turbines (Fig. S1). Accordingly, the general integral function for respondents' WTA against wind farm size is:

$$y = 22.92 * x + C \quad (8)$$

where y is WTA (£/household/year), x is the number of turbines ($2 \le x \le 40$) and C is the constant depending on the base-level of wind farm size by which the WTA is set to be zero.

Table 5
Marginal values of wind turbine height.

Study	Welfare measure	Marginal value (£/household/year)	Function	Model fitting
Dimitropoulos and Kontoleon (2009)	WTA	135 m → 75 m: −475	$y = 7.92 * (x - 75)$ $(75 \le x \le 135\ \mathrm{m})$[a]	N.A.
Brennan and Van Rensburg (2016)	WTA	80 m → 130 m: 129 80 m → 180 m: 207	$y = 258 * \ln(x/80)$ $(80 \le x \le 180\ \mathrm{m})$	$P < 0.001$ $R^2 = 0.99$
Meyerhoff et al. (2010)	WTP	n.s.		
Drechsler et al. (2011)	WTP	n.s.		
Liebe et al. (2012)_retest[b]	WTP	200 m → 150 m: n.s. 200 m → 110 m: −12.2	$y = 0.11 * (x - 110)$ $(110 \le x \le 200\ \mathrm{m})$	N.A.
Meyerhoff (2013)	WTP	200 m → 150 m: n.s. (−13.8/n.s./n.s.)[c] 200 m → 110 m: n.s.	Class1: $y = 0.276 * (x - 150)$, $(150 \le x \le 200\ \mathrm{m})$	N.A.
Mariel et al. (2015)	WTP	n.s.		
Ek (2006)	WTP	n.s.		
Vecchiato (2014)	WTP	50 m → 120 m: −27.2 50 m → 200 m: n.s.	$y = 0.39 * (120 - x)$ $(50 \le x \le 120\ \mathrm{m})$	N.A.

[a] The original attribute was the height of turbine tower (50 m, 90 m), which, as explained by the authors, corresponded to turbine height of 75 m and 135 m respectively.
[b] Liebe et al. (2012) conducted a test/retest study, here is the result of the retest survey as the test study did not contain any significant estimates for the attribute of turbine height.
[c] Results in parentheses are estimates of different latent classes of respondents.

Three WTP studies also revealed respondents' preference for smaller wind farms (Mariel et al., 2015; Meyerhoff, 2013; Oehlmann and Meyerhoff, 2017) and their WTP decreased with the number of turbines at the weighted average rate of £-1.386/household/year/turbine within the range of 4–50 turbines (Fig. S2). The corresponding general integral function is:

$$y = -1.386 * x + C \tag{9}$$

where y is WTP (£/household/year/turbine), x is the number of turbines ($4 \le x \le 50$) and C is the constant depending on the base-level of the number of turbines by which the WTP is set to be zero.

On the other hand, four WTP studies revealed the opposite preference for larger wind farms with more turbines (Mariel et al., 2015; Meyerhoff, 2013; Navrud and Braten, 2007; Vecchiato, 2014). Within a very small range of 4–6 turbines, the average increase rate of WTP is £0.60/household/year/turbine; while within the rage of 7–100 turbines, the average derivative (rate) of increasing WTP can be fitted by the function below:

$$y = 8.21/x + 0.24 \tag{10}$$

where y is $d(\mathrm{WTP})/d(\mathrm{turbines})$, x is the number of turbines ($7 \le x \le 100$). The coefficient estimation is significant at the 0.001 level and the pseudo R^2 of the model fitting is 0.97 (Fig. 7). Accordingly, the general integral function is:

$$y = 8.21 * \ln(x) + 0.24 * x + C \tag{11}$$

where y is WTP (£/household/year), x is the number of turbines ($7 \le x \le 100$) and C is the constant depending on the base-level of the number of turbines.

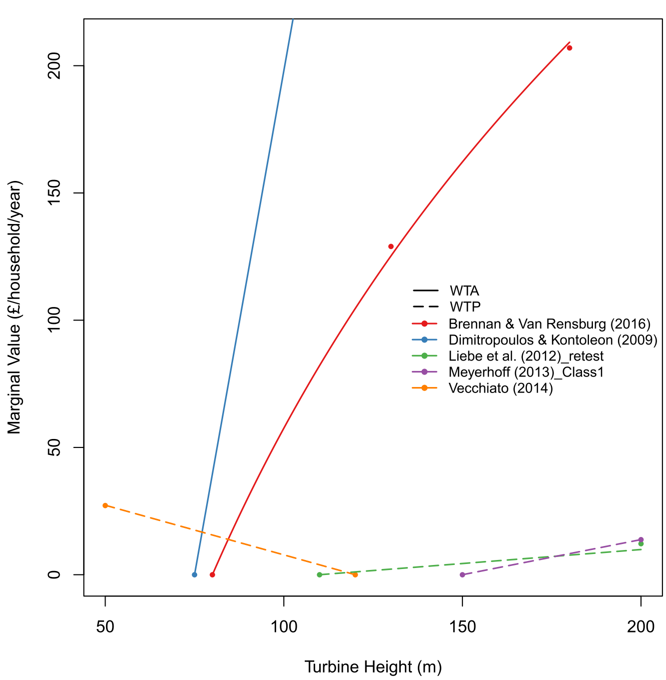

Fig. 4. Estimated marginal values (points) and fitted functions (curves/lines) of turbine height.

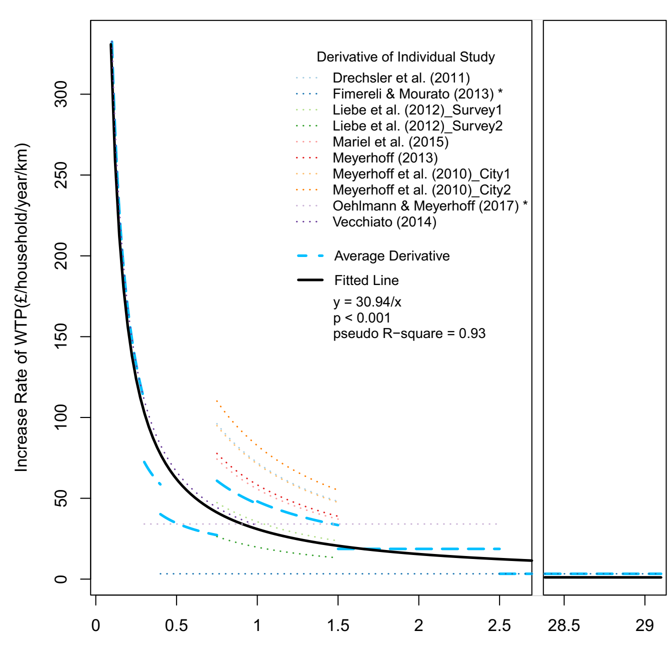

Fig. 5. Derivative functions of WTP for moving onshore wind farms to different distances. *Studies that evaluated wind energy together with other renewable energy.

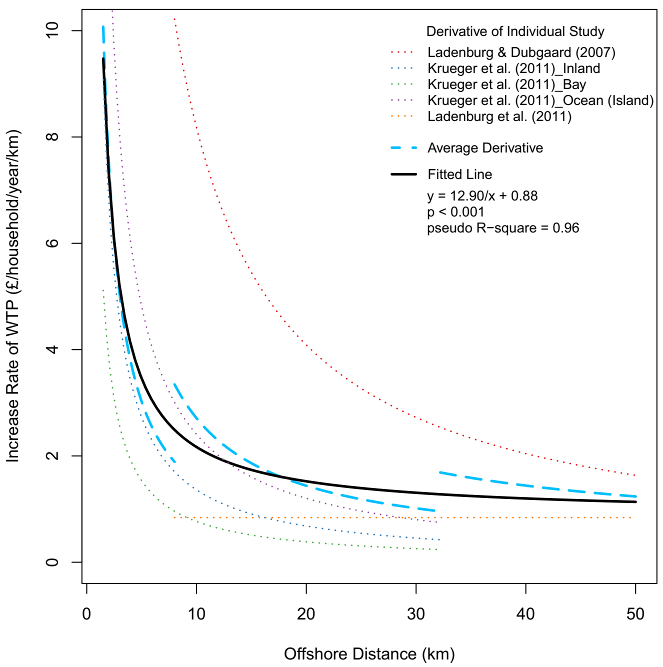

Fig. 6. Derivative functions of WTP for moving offshore wind farms to different distances.

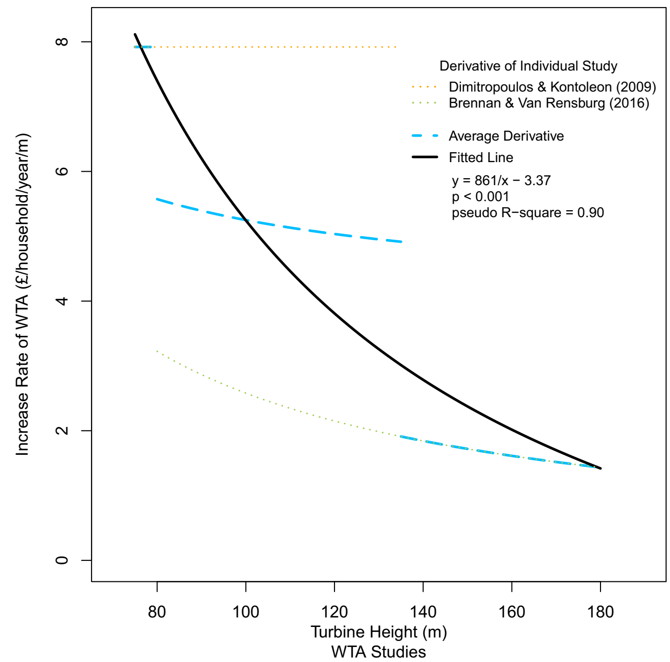

Fig. 8. Derivative functions of WTA against turbine height.

3.2.4. Turbine height

Similar with the case of the size of wind farms, divergent preferences were also found for the attribute of turbine height. For those who preferred smaller wind turbines, the average derivative of their increasing WTA against turbine height can be fitted by the function:

$$y = 861/x - 3.37 \tag{12}$$

where y is $d(\text{WTA})/d(\text{height})$ (£/household/year/m) and x is turbine height (70 m ≤ x ≤ 100 m). The coefficient estimation is significant at the 0.001 level and the pseudo R^2 of the model fitting is 0.90 (Fig. 8).

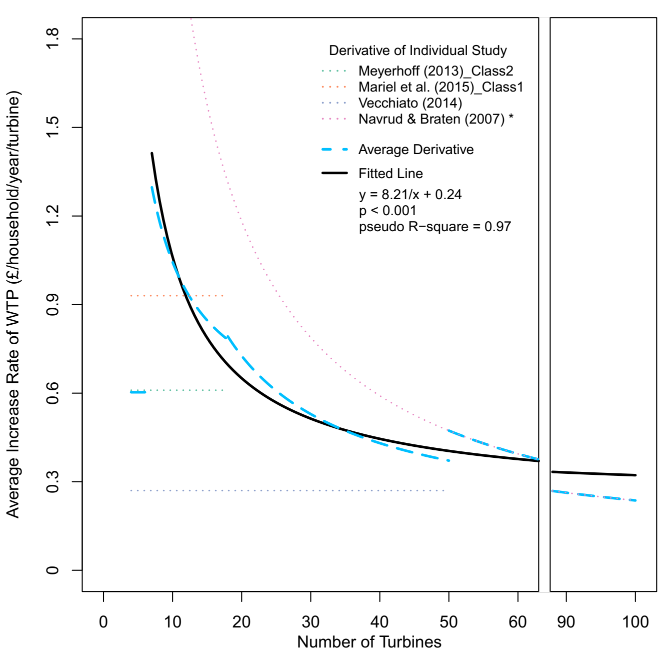

Fig. 7. Derivative functions of increasing WTP with wind farm size. *This study evaluated wind energy together with hydro power and natural gas.

Accordingly, the general integral function is:

$$y = 861 * \ln(x) - 3.37 * x + C \tag{13}$$

where y is WTA (£/household/year), x is turbine height (70 m ≤ x ≤ 100 m) and C is the constant depending on the base level of turbine height by which the WTA is set to be zero. Only one WTP study revealed similar preference for smaller turbines, thus no average derivative fitted function and general integral function were derived.

On the other hand, two WTP studies found the opposite preference for larger (higher) wind turbines and respondents' WTP increased with the turbine height at the weighted average derivative/rate of £0.156/household/year/m between 110 m and 200 m (Fig. S3). Therefore, the general integral function of increasing WTP against turbine height is:

$$y = 0.156 * x + C \tag{14}$$

where y is WTP (£/household/year), x is turbine height (110 m ≤ x ≤ 200 m) and *C* is the constant depending on the base level of turbine height whereby the WTP is set to be zero.

All the average derivative fitted functions and general integral functions of the three attributes, namely Function (4)–(14), together with the attribute range and model fit information are listed in Table S2 for interested readers.

4. Discussions

Caveats are needed to interpret and use the results of this paper due to the relatively small size of datasets to derive the nonlinear functions for individual studies and the average derivative fitted functions for multiple studies. This is largely because that there have been relatively small number of CE studies on wind farm disamenities so far and each wind farm attribute has been studied by even fewer studies. Nevertheless, the "calculus method" we proposed in this paper can be easily applied in the future when more studies and data are available and the robustness of the functions we derived to describe the effect of wind farm attributes on WTP or WTA can keep improving over time. Another reason to be cautious about the results of this paper is the various limitations of the original studies which could undermine the reliability of the estimates used in this meta-analysis. For example, over half of the original studies did not use any or used very simple visualisation for the valued wind farm attributes in their surveys, which makes the accuracy and rigorousness of their estimates questionable (Hevia Koch and Ladenburg, 2016). Despite the limitations mentioned above, this paper is promising to make methodological contribution to the literature from the following aspects.

4.1. Non-linear WTP or WTA functions for wind farm attributes

So far, the non-linear effect of wind farm attributes on WTP or WTA has only been captured by discrete estimates of WTP or WTA for different attribute levels (as reported in the Column "Marginal Value" in Table 2-5). To our knowledge, this paper is the first meta-analysis to establish non-linear functions to directly describe the non-linear effect of attributes in CE literature. For example, the "distance decay effect", i.e. the declining marginal benefits of moving wind turbines further away, has been reported in previous reviews (Knapp and Ladenburg, 2015; Ladenburg and Lutzeyer, 2012), but this paper suggests that such distance decay effect can be mathematically described by natural logarithmic functions for increasing WTP or the reciprocal of exponential functions for decreasing WTA with distance. Moreover, although two meta-analysis studies confirmed that wind farms at greater distances were preferred by respondents in different studies, they only differentiated wind farms within/out of 8 km (Mattmann et al., 2016) and 10 km (Bigerna and Polinori, 2015) respectively. In comparison, this paper provides the general integral functions of WTP against distances (Function 5 and 7), which allows interpolation of the WTP for moving wind farms to any distance within the range of 0.1 km – 29 km (onshore) and 1.5 km – 50 km (offshore). With these WTP-distance functions, it is possible to incorporate monetary valuation results with spatial and viewshed analysis to map the distribution of economic loss caused by the visual impact of wind farms (Chiang et al., 2016). Furthermore, it can be inferred from Function (4) and (6) that the WTP for locating onshore wind farms further away increases faster with distance than the WTP for offshore wind farms at the beginning, but the difference becomes smaller with the distance till 20.5 km, where the increase rate of WTP for offshore wind farms becomes higher afterwards.

4.2. An alternative method to multivariate meta-regression analysis

CE studies have been considered difficult and even unsuitable for meta-analysis due to the use of different attributes to describe varied environmental "commodities" for valuation (de Ayala et al., 2014). This paper proposes a "calculus method" as an alternative to the prevailing multivariate meta-regression analysis to synthesize CE studies. By focusing on the estimated marginal WTP or WTA for individual attributes, this new analysis method helps to reveal insights that might be missed in the current meta-analyses. For example, the attribute of turbine height was usually excluded from meta-regression analysis (Bigerna and Polinori, 2015; Mattmann et al., 2016; Mirasgedis et al., 2014) because this attribute had been evaluated by only a few CE studies, thus adding it into the meta-regression function could substantially reduce the sample size of the analysis. However, this paper managed to reveal that people had divergent preferences for tall turbines across different studies (Fig. 4). Interestingly, the results of WTP studies showed that wind turbines around 110 m to 120 m high (the size of commonly installed 1.5 MW – 2 MW turbines) happened to be the least popular turbines for both groups of people who either prefer or dislike big turbines (Fig. 4).

Even if an attribute can be included in the mainstream multivariate meta-analysis, the new analysis method proposed in this paper can provide more detailed information such as the divergent (heterogeneous) preferences. Take the size of wind farm as an example, the meta-analysis of Mattmann et al. (2016) indicated that large wind farms (with more turbines) generally resulted in greater disamenities to respondents. In comparison, this paper not only suggested that public opinions about the size of wind farms were divergent (Fig. 3) but also provided separate WTP and WTA functions for the two groups of people with divergent preferences (Section 3.2.3). Given that understanding the heterogeneity of public preferences is one of the major research topics in many CE studies, the analysis method proposed in this paper may be a better option than the current multivariate meta-analysis technique for synthesizing this type of literature.

4.3. Implication to future meta-analysis and choice experiment studies

Multivariate linear functions are widely used in meta-analysis based on the simplified assumption that there are linear relationships between the independent variables (e.g. wind farm attributes) and the dependent variable (e.g. WTP or WTA). However, this paper suggests that attributes like distance are more likely to exhibit non-linear effect on the WTP or WTA. Therefore, it is worth trying to introduce non-linear components of wind farm attributes into future multi-variate meta-analyses to better reflect the findings from literature. Similarly, the sum of linear components of attributes has long been used in CE studies to establish the utility functions to describe respondents' preference whereas the nonlinear effect of attributes have only been described by using multiple dummy variables to represent different levels of the attributes. Since this paper has shown that the non-linear effect of certain attributes (e.g. distance) can be directly described by nonlinear functions (e.g. natural logarithm function), it would be worthwhile examining if directly introducing the non-linear components into the utility function can improve the model fitting and efficiency in CE studies.

5. Conclusions

This paper applied an innovative "calculus method" to synthesize the valuation results of CE studies on the visual impact of wind farms. Analysis was focused on the estimated WTP and WTA for three wind farm attributes, namely the distance from the wind farm to residential or coastal areas, the size of wind farm (in terms of the number of wind turbines) and turbine height. Regression functions of WTP or WTA against the three attributes were established for individual studies, then the average derivatives of the WTP or WTA functions of multiple studies were used to derive the general integral functions to describe the overall effect of the wind farm attributes on WTP or WTA across the reviewed studies.

Our results show that respondents' preferences for locating wind farms further away from residential or coastal areas and the "distance decay" effect on WTP can be mathematically described by natural logarithm functions. Moreover, people showed divergent preferences for the size of wind farms (the number of turbines) and turbine height, thus separate WTP or WTA functions were derived to describe the two opposite preferences.

This paper contributes to the literature by using non-linear regression to directly capture the non-linear effect of wind farm attributes on WTP or WTA and introducing an alternative method to the prevailing multivariate regression meta-analysis for synthesizing CE studies. The general integral functions of WTP or WTA against wind farm attributes we derived in this paper can be used for spatial modelling of the environmental cost of wind energy development and benefit transfer studies in the future. Although this paper focuses on the visual impact of wind farms, our method can be widely applied in meta-analysis of CE studies in other research areas.

Acknowledgments

This study has been carried out under the Addressing Valuation of Energy and Nature Together (ADVENT) Program, funded by Natural Environment Research Council (NE/M019705/1), UK.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.04.430.

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