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Consumer's Willingness to Pay for Green Electricity: A Meta-Analysis of the Literature

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Consumer's Willingness to Pay for Green Electricity: A Meta-Analysis of the Literature*

Swantje Sundt and Katrin Rehdanz

Abstract:

The number of studies published focusing on people's preferences for green electricity has increased steadily, making it more and more difficult to identify key explanatory factors that determine people's willingness-to-pay (WTP). Based on results of a meta-regression our results indicate e.g. that hydropower is the least preferred technology. Variables such as information on the type of power plant that will be replaced by renewables, which are often omitted from primary valuation studies, are important in explaining differences in values as well. When assessing the predictive power of our results for out-of-sample value transfers we find median errors of approximately 30%, depending on model specification.

Keywords: meta-analysis, renewable energy, valuation, value transfer, willingness to pay

JEL classification: C53, D62, Q40, Q48, Q51

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1. Introduction

Many industrialised countries have ambitious renewable energy targets to mitigate climate change and/or to gain independence of fossil fuel imports. At present, electricity generated from power plants using renewables is more costly compared with those using conventional fuels. The difference is paid for by the consumers either directly through a higher price for renewable energy or indirectly through taxes. As a response to this, a number of studies have investigated consumer preference and willingness to pay (WTP) for larger shares of green electricity (most recently, Kim et al., 2013). The number of such studies published over the last few years focusing on people's preferences for renewables has increased steadily, thus resulting in a flood of data, which has made it increasingly more difficult to identify key explanatory factors that determine people's WTP for renewables. Studies vary widely in the energy-related characteristics they analyse (such as energy mix, siting of new power plants, infrastructure investments, etc.), the geographical location and the valuation technique employed.

Meta-analysis is a quantitative analysis of summary indicators reported in a series of similar empirical studies (Stanley, 2001). A quantitative meta-analysis ensures global comparability of WTP for renewable energy and provides evidence for global preferences. In our meta-analysis, we investigate the mean WTP per household and month and per kilowatt-hour to determine global preferences for renewable energy. Based on a meta-regression, we analyse whether differences in WTP exist by country, whether results on exploratory variables for WTP differ and the extent to which survey design influences WTP estimates. Because costs associated with performing a study that assesses WTP for green electricity are considerable, we explore the use of "value transfer" to non-valued sites/countries as an alternative to primary valuation.

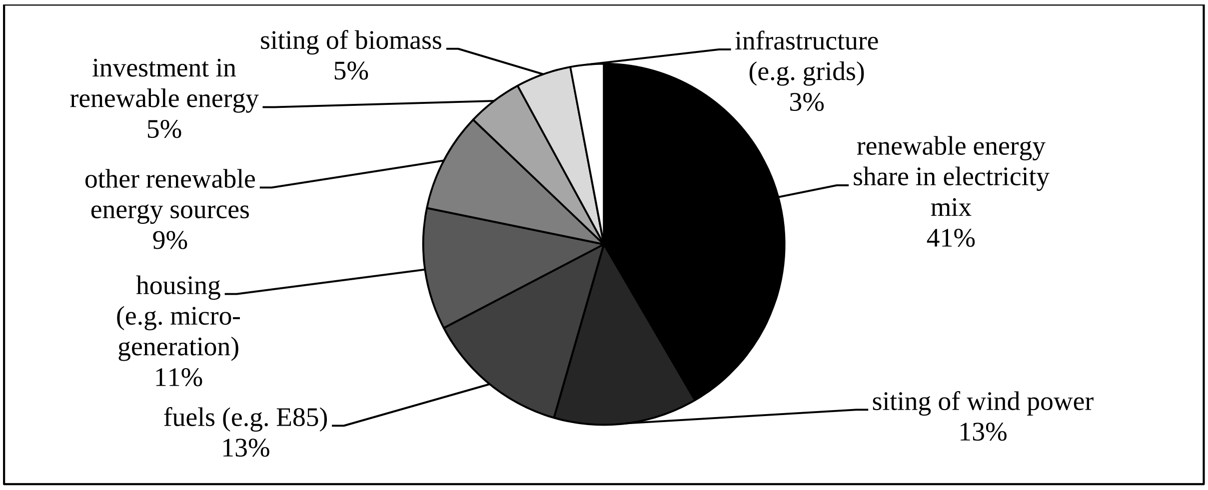
Previous meta-analyses on preferences for renewable energy focus primarily on public acceptance of wind power (e.g., Aitken, 2010) and on the corresponding "not in my backyard" (NIMBY) phenomenon (van der Horst, 2007). While meta-analysis in combination with meta-regression is often used in ecosystem valuations (e.g., coral reefs: Brander et al., 2007), to our knowledge, there does not exist a meta-regression analysis on WTP for renewable energy.

The structure of our paper is as follows. Section 2 reviews the literature regarding consumer WTP for renewable energy in the electricity mix and outlines the type of studies used in our analysis - those focusing on green electricity. Section 3 presents our data and describes results of individual studies as well as summary statistics of WTP estimates. Section 4 presents the specification of the meta-regression, and the methods used to judge quality of the value transfer. Section 5 discusses the results of the meta-regression, and explores the validity, efficiency and robustness of our results when transferring values. Section 6 concludes the paper.

2. Overview of the willingness-to-pay for renewable energy literature

We collected 101 studies based on stated preference surveys that estimated respondents' WTP for renewable energy. The WTP, therefore, is either captured by contingent valuation analysis or estimated via choice experiments (including conjoint analysis). These studies are classified as presented in figure 1.

Figure 1: Key aspects of WTP estimation of the 101 stated preference studies.



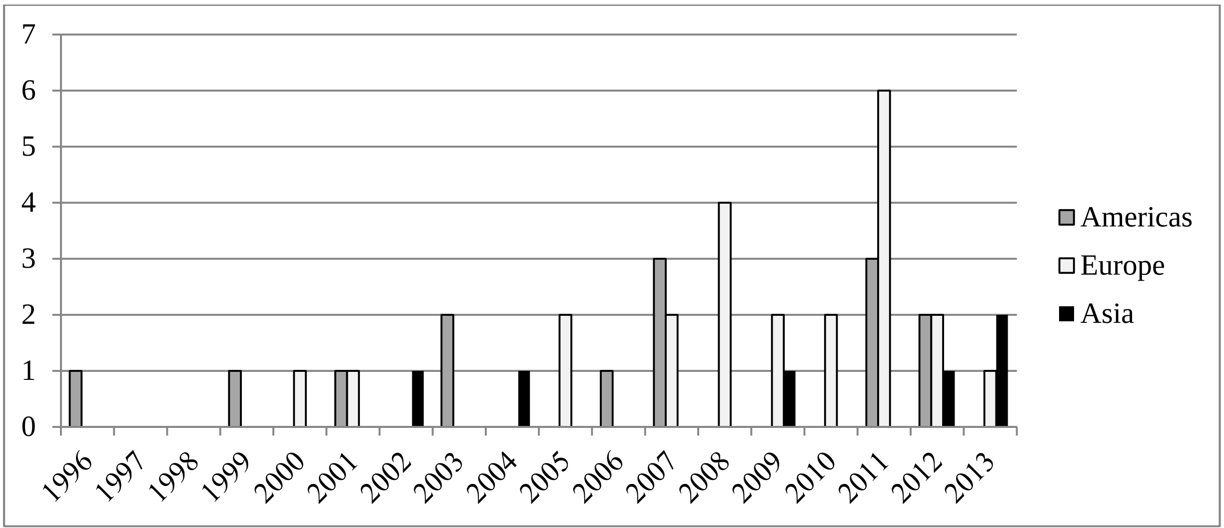
Source: Own presentation.

In the following, we focus on the largest category by investigating those 43 studies that focus on people's WTP for larger shares of renewables in the electricity mix. These studies are more readily comparable in a meta-analysis than a larger set of studies characterised by other key aspects including studies that, for example, focus on the choice of location for specific renewables or particular fuel types such as E85.

The earliest study in the category 'electricity mix' was published by Farhar and Houston (1996). They measured the WTP for electricity from renewables in the United States (US). Between 1996 and 2006, only one or two studies per year were published. After 2006, the number of publications increased, with an average of 4.4 studies per year being published between 2007 and 2013, most of them with a focus on European countries or regions.

Figure 2 shows that over space and time, studies are very unevenly distributed. Overall, we count 23 studies for Europe, twelve for the Americas and six for Asia. At the country level, most of the surveys were conducted in the US (twelve publications), followed by Germany (seven publications) and the United Kingdom (UK, four publications). While studies using data for the US or the UK are relatively evenly distributed over time, the first studies using German survey data were published in 2005 (Menges et al., 2005; Gossling et al., 2005).

Figure 2: Number of published studies by year and continent.



Source: Own presentation.

Over time, researchers considered that more factors were involved in determining people's WTP, and the information they used provided increasingly more insight. For instance, several authors reviewed the influence of payment arrangements on the WTP for renewable energy, e.g., Menges and Traub (2008), Solino et al. (2009) and Solino et al. (2012). Other authors compared the current electricity mixes with stated consumer preferences, e.g., Grösche and Schröder (2011) and Kaenzig et al. (2013).

3. Description of data

Among the 43 studies, we exclude 25 from the meta-regression because of sample selection bias (e.g., Gossling et al. 2005) or unsuitable units of WTP estimates; that is, inconvertible. For instance, some authors express WTP as a percentage of the current electricity bill (e.g., Liu et al. 2013) or as the probability to be willing to pay anything at all (e.g., Batley et al., 2001). Further, we exclude one survey conducted in India (Chakrabarti & Chakrabarti, 2002). This study focused on rural electrification and, to a much lesser extent, on India's electricity mix.

Our final meta-regression consists of 85 WTP values that are ascertained from 18 studies (see Table 1). This corresponds to an average of 4.72 WTP values per study. We abstract the largest data sample (19 observations) from the study by Borchers et al. (2007), a choice experiment eliciting preferences for electricity for different renewable energy sources that was conducted in Newcastle County, Delaware, USA. To avoid overweighting WTP values of individual studies, we use weights. First, because WTP values of one study could systematically deviate from the real WTP, and second, because some studies provide WTP values describing similar situations (e.g., an increase of 10% of renewables compared with an increase of 20%). One study used a latent class model to estimate WTP (Cicia et al., 2011). Estimating a latent class model includes estimating the probability of being a member of one of these classes. To take these data into account, we weight the particular classes with the stated class probability. Furthermore, two studies (Bigerna & Polinori, 2011; Kosenius & Ollikainen, 2012) are working papers. Because omitting these two studies does not change the results of our analysis (presented in Section 5), we retain them in our sample.

Table 1: Studies included in the meta-regression.

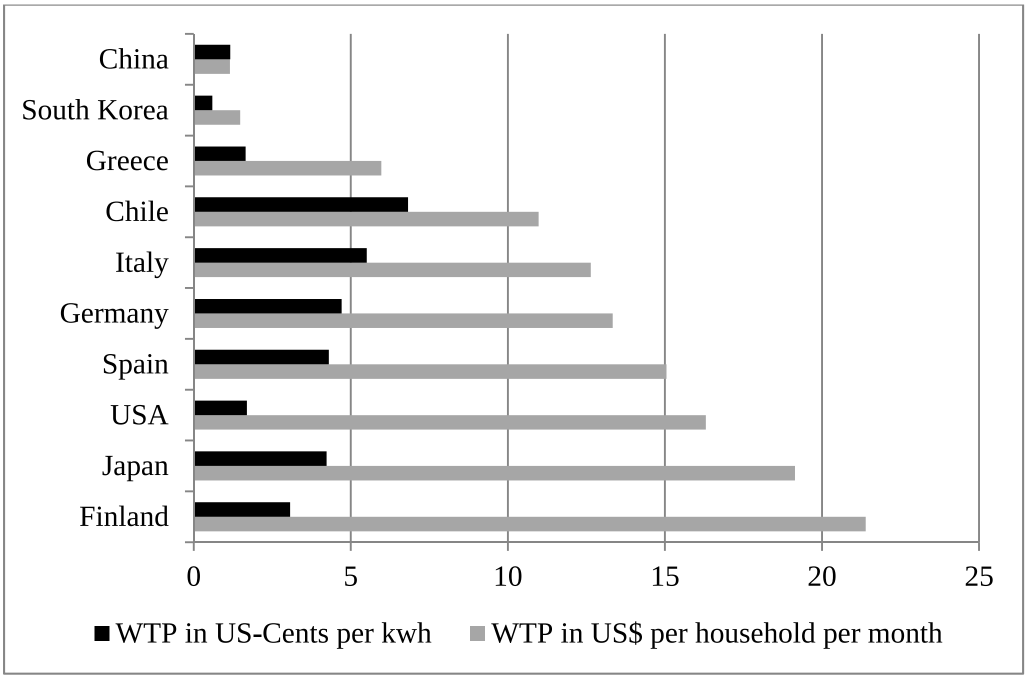
Author (year)	Year of Survey	Country	Coverage	Method	# WTP values
Aldy et al. (2012)	2011	US	national	CV	3
Aravena et al. (2012)	2008	Chile	local	CV	4
Bigerna & Polinori (2011)	2007	Italy	national	CV	9
Bollino (2009)	2006	Italy	national	CV	9
Borchers et al. (2007)	2006	US	local	CE	19
Cicia et al. (2011)	2009	Italy	national	CE	3
Gracia et al. (2012)	2009	Spain	local	CE	3
Hanemann et al. (2011)	2009	Spain	national	CV	1
Kaenzig et al. (2013)	2009	Germany	national	CE	3
Kim et al. (2013)	2008	South Korea	national	CV	4
Komarek et al. (2011)	2009	US	local	CE	9
Kosenius & Ollikainen (2012)	2008	Finland	national	CE	6
Nomura & Akai (2004)	2000	Japan	national	CV	3
Solino et al. (2009)	2006	Spain	regional	CV	4
Susaeta et al. (2011)	2008	US	regional	CE	1
Yoo & Kwak (2009)	2008	South Korea	local	CV	2
Zhang & Wu (2012)	2010	China	regional	CV	1
Zografakis et al. (2010)	2007	Greece	regional	CV	1

Source: Own presentation;
CV: Contingent Valuation Method; CE: Choice Experiment / Conjoint Analysis.

The 18 studies were published in 2004, 2007 or between 2009 and 2013. The corresponding surveys were conducted in ten countries on three continents (Europe, the Americas and Asia) either in 2000 or between 2006 and 2011. Multiple surveys were conducted in the US (3), Spain (3), Italy (3) and South Korea (2). One-half of the surveys were national, one-quarter were local and another quarter were regional. Each study in our sample used either contingent valuation techniques (twelve studies) or choice modelling approaches (six studies) to determine WTP. Overall, we collect 85 WTP values, 41 of which are gained by contingent valuation analyses and 44 by choice modelling.

Our dependent variable is the WTP for an increase in renewable energy in the current electricity mix. While results of contingent valuation studies are most often expressed as mean WTP, results of choice experiments are expressed as marginal WTP. If the “status quo” option belongs to the selectable alternatives of the choice experiment and the marginal WTP is based on the “status quo”, we treat the marginal WTP as the mean WTP. Further, we use only WTP values in the meta-regression that can be interpreted as “WTP for a higher renewable energy share in the current electricity mix” and measure in fixed units of currency per time frame and household. Next, we approximate the WTP per kilowatt-hour to adjust the WTP to average electricity usage per capita.[1] A remarkable fact is the relatively high electricity consumption per capita in Finland and the US, which is at least twice as high as the electricity consumption of Japan, the third highest in the sample.

Figure 3: Mean WTP by country.



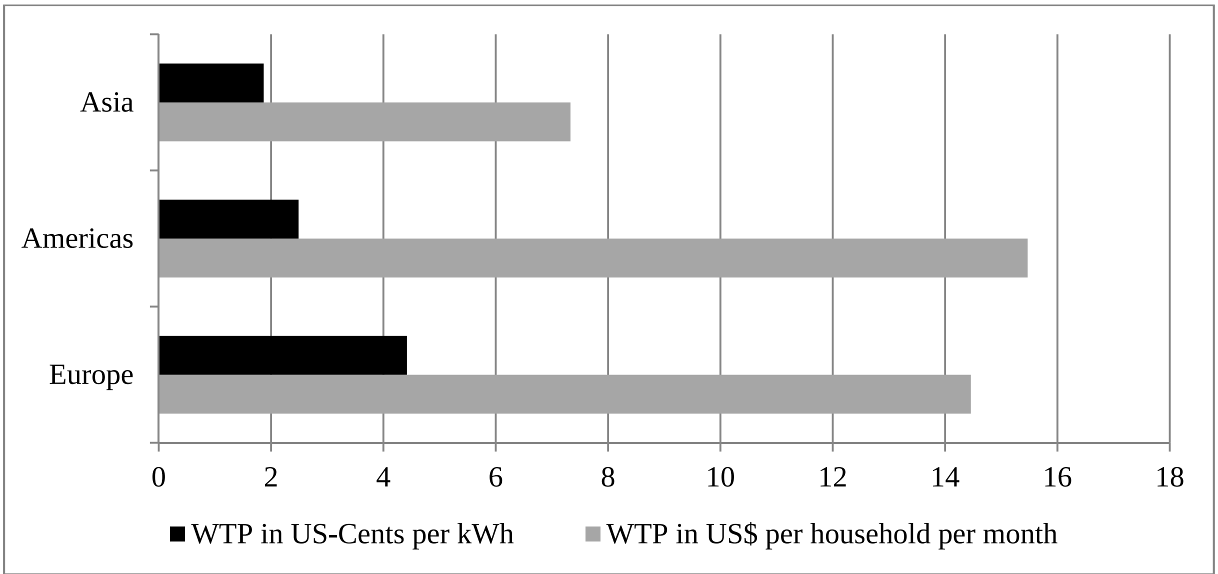
Source: Own presentation.

[1] For this, we used information on total residential energy consumption and total population (OECD/IEA, 2014a/b), as well as information on average household size (Eurostat, 2013; U.S. Census Bureau, 2013; OECD, 2012; Statistics Japan, 2013; National Bureau of Statistics China, 2010).

To ensure comparability, we convert WTP values in US$ per household per month and adjust them to 2010 prices using purchasing power parity exchange rates.[2] In our sample, the mean WTP for a higher renewable energy share in the electricity mix is US$ 13.13 per household per month and the median WTP is US$ 11.67. The lowest WTP (US$ 1.00) is found by Borchers et al. (2007) for an increase in biomass in the US. Hanemann et al. (2011) report the highest WTP (US$ 43.01) for an increase in renewables in Spain. Overall, the distribution of WTP values is positive skewed. When WTP is measured in kilowatt-hours, the mean WTP is US-Cents 3.18/ kilowatt-hour and the median WTP is US-Cents 1.95/ kilowatt-hour.

At the country level (see Figure 3), the highest mean WTP per household (US$ 21.39), which corresponds to a mean WTP per kilowatt-hour of US-Cents 3.07, is observed for Finland. However, we observe the opposite for Chile, the country with the second lowest residential energy consumption per capita. Here, the WTP per household (US$ 10.98) is below average while the WTP per kilowatt-hour (US-Cents 6.82) is ranked highest. Furthermore, China and South Korea have the lowest WTP per household and per kilowatt-hour.

Figure 4: Mean WTP by continent.



Source: Own presentation.

Although Japan demonstrates an above average WTP per household, the average WTP for Asia (see Figure 4) is half that of European countries and countries in the Americas, which are quite similar. With respect to the average WTP per kilowatt-hour, the WTP for Asia is the lowest. However, in contrast to the WTP per household, there exists a significant difference between the mean WTP for the Americas (US-Cents 2.49) and for Europe (US-Cents 4.43).

[2] Data retrieved from OECD (n.d.).

Several hypotheses exist regarding the factors that explain the differences in the studies' WTP values. In our sample, most studies include income as an exploratory variable. Of the 18 studies, only two present evidence for a slightly negative influence of income on WTP (Borchers et al., 2007; Susaeta et al., 2011). All others find a positive effect of income on WTP.

Frequently, age and price variables are considered as well. In general, older people seem to have a lower WTP, but Aldy et al. (2012) find the opposite. Borchers et al. (2007) distinguish different age groups and find people over 50 years of age and below 30 years of age reported a lower WTP. This finding could be correlated with the positive effect of income, which is lower for these groups. The effect of prices is always negative.

Half of the studies explain differences in studies' WTP values by gender, education or environmental attitudes, such as a belief in climate change. With respect to gender, in all studies, WTP is lower for male than for female respondents. Education has a positive effect on WTP. An exception, however, is Yoo and Kwak (2009). Not surprisingly, environmental concerns increase peoples' WTPs. Borchers et al. (2007) find a negative effect on WTP when respondents are more concerned about the environmental impacts of electricity generation.

Some authors include alternative renewable energy sources, knowledge about renewable energy or regional aspects. Overall, renewable energy sources increase WTP for electricity. Borchers et al. (2007) and Gracia et al. (2012) find evidence that electricity generated from solar is preferred over other alternatives. While US-Americans exhibit a positive WTP for nuclear power (Borchers et al., 2007), Germans prefer the electricity mix with a 25% share in natural gas over the mix with a 25% share in nuclear power (Kaenzig et al., 2013).

Studies that consider knowledge about renewable energy show varying results, which can be explained by the various ways in which knowledge is controlled. For example, Bollino (2009) uses factual questions about renewable energy, and participants who answer these questions correctly tend to exhibit lower WTP values. Kim et al. (2013) obtain similar results when eliciting peoples' knowledge of the ratio of renewables in total energy generation. However, participants who demonstrate awareness of the fact that electricity can be generated from photovoltaic and biomass report higher WTPs (Zografakis et al., 2010).

While six studies compare WTP by region, the results are survey specific. For example, Kosenius and Olikainen (2012) distinguish WTP for woody biomass by East Finnish and all other Finnish people. In East Finland, the WTP for forest biomass is higher than it is in the rest of Finland. The authors contend that this is due to the high forest coverage of East Finland. Kim et al. (2013) state a lower WTP for people living in rural areas of Korea. Susaeta et al. (2011) find no differences in WTP when comparing the US-states Arkansas, Florida and Virginia.

Furthermore, in our sample, only four studies take household characteristics into account, including, e.g., Aldy et al. (2012) and Bigerna and Polinori (2011), who find a decreasing WTP for larger households.

4. Meta-analysis and value transfer

4.1. Meta-regression model

In our meta-regression, we investigate the marginal effects of different study designs on the WTP for a higher renewable energy share in the electricity mix. In our model, the dependent variable is a vector y, which contains either WTP values measured in US$ per month per household in 2010 prices or WTP values measured in US-Cents per kilowatt-hour. The independent variables (table 2) belong to two matrices. Matrix X_C includes country-specific characteristics; matrix X_S includes survey-specific characteristics. Country-specific characteristics contain information on a country's renewable energy share in total energy production for a given survey year differentiated by hydropower and other renewable energy sources (OECD/IEA, 2014a). Survey-specific characteristics are captured by a set of dummy variables controlling for the valuation method, the design of the WTP scenario, and the exploratory variables considered in the original WTP estimation.

We improve the quality of the estimation results by taking the natural logarithm of the dependent variable. This leads to the following semi-log linear regression model:

$$\ln(y_i) = \alpha + \beta_C X_{Ci} + \beta_S X_{Si} + \varepsilon_i \qquad (1)$$

where α is a constant term, β_C and β_S are vectors of coefficients that contain information about the marginal effects, ε_i is the error term corresponding to WTP value y_i with $i = 1, \dots, n$ and n is the number of extracted WTP values. We use weighted linear regression with robust standard errors to account for dependencies in observations provided by the same study, or dependencies in regions. We prefer linear regression over panel models because in the fixed effects model all exploratory variables are omitted and in the random effects model the hypothesis that there do not exist random effects cannot be rejected at a 5%-significance level.

Table 2: Exploratory variables of meta-regression.

Variable	Definition
YEAR	Year of survey, base 2000
RE_SHARE	Percentage share renewables of total energy production (without hydro)
HYDRO_SHARE	Percentage share in hydro power of total energy production
LN_RE	Ln of percentage share renewables of total energy production (without hydro)
LN_HYDRO	Ln of percentage share in hydro power of total energy production
RE_SQUARE	Squared percentage share renewables of total energy production (without hydro)
HYDRO_SQUARE	Squared percentage share in hydro power of total energy production
USA	Dummy: 1 = USA; 0 = Other country
METHOD_CV	Dummy: 1 = Contingent valuation; 0 = Choice experiment
UN_SPEC	Dummy: 1 = No specification which kind of power plant should be substituted; 0 = Specified
ATT_KNOW	Dummy: 1 = Knowledge about RE included in WTP estimation; 0 = Not included
ATT_PRICE	Dummy: 1 = Price variable included in WTP estimation; 0 = Not included
ATT_HH	Dummy: 1 = Household variable included in WTP estimation; 0 = Not included
ATT_INC	Dummy: 1 = Income variable included in WTP estimation; 0 = Not included
ATT_EDU	Dummy: 1 = Education included in WTP estimation; 0 = Not included

Source: Own presentation.

It is plausible to assume that the survey design has a significant influence on the estimated WTP. In our case, either contingent valuation or choice modelling is used to elicit WTP. Previous studies that compared results from contingent valuation and choice experiments (e.g., Hanley et al., 1998; Danyliv et al., 2012) report higher WTP in choice experiments. The dummy variable *METHOD_CV* controls for methodology because in our sample, the mean WTP from contingent valuation studies is lower as well. Further, as we expect the WTP scenario to influence WTP estimates, we add the dummy variable *UN_SPEC* to identify those observations where information on the substitute for the renewable is missing.

Further, we suspect an influence by the kind of variables which are chosen as exploratory variables to estimate WTP; e.g. *ATT_EDU* identifies those observations where information of a respondent’s education level was controlled for. .

4.2. Quality of value transfer

Environmental value transfer (see Brouwer, 2000) is often used to adapt results from previous surveys from a study site to a policy site. A main advantage of environmental value transfer is its low cost compared with a primary valuation study at the policy site.

Three general approaches exist to transfer values - direct value transfer, benefit function transfer and meta-analysis. Using direct value transfer, the study site and the policy site should be similar in their characteristics (otherwise adjustments are necessary) as estimated value(s) of one or more primary studies are simply transferred to the policy site. With respect to function value transfer, the second approach, values are transferred to a policy site based on the site's own characteristics using the value transfer function of the study site. Here, we follow the third approach by using results of a meta-analysis to transfer values. Comparing the three approaches, value transfer based on meta-analysis has the advantage of using information from a number of studies. Also, it tends to perform better (Rosenberger and Phipps, 2002; Engel, 2002).

Despite value transfer based on meta-analysis being the preferred approach, this type of value transfer might produce substantial transfer errors as well. This is particularly the case when the data underlying the estimated relationship in the meta-regression does not represent well the site to which values are being transferred to. Other types of errors occur, because dummy variables do not capture the true variation in the characteristics they are supposed to measure. Further, it is often difficult to capture important quality and/or quantity differences across studies (e.g., as they relate to the description of the primary WTP scenario). Finally, primary valuation studies are also a source of errors.

To test the out-of-sample forecast performance of our models. Similar to Brander et al. (2006), who implement a value transfer on wetlands, we use a $n-1$ data splitting technique to estimate n meta-regression transfer functions. Each function is based on $n-1$ observations, to predict the WTP[3], $\hat{y}_i$ for the omitted study. As suggested and explained by Shrestha and Loomis (2001, 2003), we explore the validity of this predicted WTP by using two Student's t-tests, which test for equal means and for correlation, by investigating the absolute (percentage) error and by regressing observed WTP on predicted WTP.

First, we perform a paired Student's t-test which inspects whether the mean of the predicted values is significantly different from the mean of the observed values. This leads to the following null hypothesis: $H_0\colon 1/n \sum_{i=1}^{n}(y_i - \hat{y}_i) = 0$; that is, on average there is no difference between predicted values and the observed value from a specific study. The hypothesis can be rejected if the value of the test statistic is larger than a previously defined significance level. If we reject the null hypothesis there is evidence that our meta-regression is incorrect.

[3] Because of the semi-log-linear model we need to adjust the predicted WTP ($\hat{y}$) for the estimated variance $\widehat{\sigma^2}$, which is the squared Root-MSE: $\hat{y} = \exp\{x\hat{\beta} + \widehat{\sigma^2}/2\}$ (Greene, 2012).

Second, we perform another Student's t-test to analyse the significance of Pearson's correlation coefficient. Pearson's correlation coefficient $r \in [-1,1]$ measures the linear correlation of two metric asymptotically normal distributed variables, whereupon, a large positive value corresponds to a strong linear correlation between predicted and observed WTP value. The null hypothesis of the Student's t-test is: $H_0: r(y, \hat{y}) = 0$. Thus, if the p-value is significant the null hypothesis has to be rejected, and there is, indeed, a significant correlation between both values.

Third, we evaluate the quality of the value transfer by calculating the absolute (percentage) error and the mean absolute percentage error; defined as: $MAPE = 1/n \sum_{i=1}^{n} |(y_i - \hat{y}_i)/y_i|)$. *MAPE* is commonly used to judge on the quality of the average forecasting performance of meta-regression value transfer functions (e.g. Brander et al., 2006).

Forth, we investigate the linear relationship of the observed WTP and the predicted WTP by performing an ordinary least squares regression by using the following model:

$$\ln(y_i) = \alpha + \beta \widehat{\ln(y_i)} + \varepsilon_i \quad (2)$$

In case of a perfectly forecasting meta-regression transfer function (equation 1), the estimated parameters are $\alpha = 0 \wedge \beta = 1$. We test this null hypothesis with a standard t-test, whereupon significance is equivalent to a biased value transfer.

5. Results

5.1. Meta-regression

Table 3 presents the meta-regression results for the two dependent variables (*LN_WTP* and *LN_WTP_KWH*) and the three models. The models differ with respect to the share in total energy production of the variables for renewable energy and hydropower. Model 1 uses the percentage shares (*RE_SHARE* & *HYDRO_SHARE*), Model 2 uses the natural logarithm of the shares (*LN_RE* & *LN_HYDRO*) and Model 3 uses, in addition to the specifications in Model 1, the squared percentage shares (*RE_SQUARE* & *HYDRO_*SQUARE).

Model 1 is our preferred model for estimating WTP per household and month (*LN_WTP*). Model 2 fails the Ramsey RESET test (Ramsey, 1969) and is not further considered. While Models 1 and 3 both explain approximately 82% of the variance in the data, the postestimation tests (F-test on joint significance of the linear and squared variables) reject the specification used in Model 3. Therefore, we exclude Model 3 from further analysis as well.

Model 2 is our preferred model for estimating WTP per kilowatt-hour (*LN_WTP_KWH*), a unit which adjusts for differences in household size and monthly electricity consumption. The coefficients for *USA* and *METHOD_CV* are both insignificant. Both other models, Model 1 and Model 3, fail to pass the Ramsey RESET test and are not further considered.

Table 3: Results of meta-regression by model.

	LN_WTP			LN_WTP_KWH		
Variable	**Model 1**	Model 2	Model 3	Model 1	**Model 2**[a]	Model 3
YEAR	**-0.3729*** **	-0.2021***	-0.3737***	-0.2737***	**-0.1878*** **	-0.2806***
RE_SHARE	**0.2432*** **	-	0.0679***	0.1640***	**-**	0.2958***
HYDRO_SHARE	**-0.0537*** **	-	0.0636*	-0.0339**	**-**	-0.0325
LN_RE	**-**	2.1097***	-	-	**1.8231*** **	-
LN_HYDRO	**-**	-1.7533***	-	-	**-1.4966*** **	-
RE_SQUARE	**-**	-	-0.0024	-	**-**	-0.0070*
HYDRO_SQUARE	**-**	-	0.0010	-	**-**	-0.0000
USA	**2.1829*** **	1.1738***	2.1399***	0.5803**	**0.0684**	0.4861*
METHOD_CV	**0.9574*** **	0.1014	0.8711**	0.8378**	**0.3155**	0.6661
UN_SPEC	**-2.5297*** **	-1.0690***	-2.3252***	-2.3509***	**-1.2741*** **	-1.8991***
ATT_KNOW	**-0.4982*** **	-0.6207***	-0.5021**	-0.5940***	**-0.5537*** **	-0.4742**
ATT_PRICE	**-1.3182*** **	-1.3913**	-1.2934***	-1.0359***	**-1.0211*** **	-0.8776***
ATT_HH	**-1.7468*** **	-1.4147***	-1.7369***	-1.6234***	**-1.4443*** **	-1.5819***
ATT_INC	**1.3823*** **	1.2021***	1.3232***	1.2445***	**1.0161*** **	1.1076***
ATT_EDU	**1.1188*** **	0.3925	1.1503***	1.1663***	**0.9050** **	1.2374***
Constant	**4.6436*** **	2.6864***	4.5141***	3.0487***	**1.3729*** **	2.5073***
F-statistic	**163.19**	122.12	364.53	65.15	**137.45**	114.49
R^2	**0.8222**	0.7381	0.8240	0.7353	**0.7426**	0.7552
Root-MSE	**0.4952**	0.6009	0.4996	0.5455	**0.5380**	0.5319
RESET (p-value)	**0.8670**	0.0000	0.2658	0.0219	**0.8230**	0.0018

n=85

Significance: *: 10%-level; **: 5%-level; ***: 1%-level

[a] We re-estimated model 2 without *USA* and *METHOD_CV*, what leads to very slight changes of coefficient size but provides no further information.

Source: Own calculations.

For ease of interpretation, we report the marginal effects in Table 4, which is Euler's number to the power of the coefficient. The marginal effect indicates that a one percentage point increase in green electricity production increases the WTP per household (in log) by factor 1.2753 (*RE_SHARE*) while a one percentage point increase in hydropower decreases the WTP by factor 0.9477 (*HYDRO_SHARE*). We discriminate between hydropower and other renewables because further inspections of the data reveal that all other renewable energy sources demonstrate positive effect on WTP. The negative effect for hydropower could be related to its large share in total renewable energy production (between 78 and 91%) in the Asian countries and in Chile.

Further, our results indicate that WTP decreases over time (*YEAR*). The marginal effect of a survey conducted in the US is pronounced for WTP per household (*LN_WTP*). However, the effect is insignificant for WTP measured in kilowatt-hour (*LN_WTP_KWH*). This is as anticipated given that the electricity consumption of an average US-household is at least twice as high as that of all other investigated countries' households, other than Finland.

Table 4: Marginal effects on WTP.

	Marginal effect on WTP per	
	household & month	kilowatt-hour
Variable	Model 1 (LN_WTP)	Model 2 (LN_WTP_KWH)
YEAR	0.6887***	0.8288***
RE_SHARE	1.2753***	-
HYDRO_SHARE	0.9477***	-
LN_RE	-	6.1907***
LN_HYDRO	-	0.2239***
USA	8.8723***	*1.0708*
METHOD_CV	2.6049***	*1.3709*
UN_SPEC	0.0797***	0.2797***
ATT_KNOW	0.6076***	0.5748***
ATT_PRICE	0.2676***	0.3602***
ATT_HH	0.1743***	0.2359***
ATT_INC	3.9841***	2.7624***
ATT_EDU	3.0610***	2.4720**
n=85		
Significance: *: 10%-level; **: 5%-level; *: 1%-level		

Source: Own calculations

In studies where information is not provided on the substitute for renewables (*UN_SPEC*), the WTP is lower. The positive effect of a contingent valuation study (*METHOD_CV*) on WTP per household is a priori unexpected as evidence suggests that choice experiments overestimate WTP in comparison to contingent valuation studies. However, in our sample, choice experiments are, for the most part, based on choice sets that specify alternative energy types. In contrast, contingent valuation studies rarely provide such information, a fact that is confirmed by the significant negative Spearman's correlation coefficient of the variable *UN_SPEC* and the dummy variable *METHOD_CV*. The marginal effect of *UN_SPEC* reduces the expected WTP value more than the marginal effect of *METHOD_CV*. Therefore, one can expect a smaller WTP per household value for a contingent valuation study compared with a choice experiment. Furthermore, the insignificance of *METHOD_CV* on the WTP per kilowatt-hour model indicates that the differences in WTP estimates between contingent valuation and choice experiments disappear once the WTP is converted, thus indicating that it is independent of an individual's status quo, e.g., monthly electricity expenditures.

The results for the dummies controlling for exploratory variables in the original studies (*ATT_**) point to significant effects for almost all controls. Studies that do not control for income as an explanatory variable (observations with *ATT_INC* value zero) report significantly lower mean WTP compared to those that control for income. Controlling for education in the original study (*ATT_EDU*), has a positive effect, while control variables for price information (*ATT_PRICE*), household characteristics (*ATT_HH*) or knowledge about renewables (*ATT_KNOW*), are negative.

5.2. Value Transfer

5.2.1. WTP per household

Using WTP per household and month (model 1, full data set) as dependent variable, the mean difference in predicted and observed WTP is 0.39 US$ per household and month. Judged on Student's t-test the null hypothesis cannot be rejected; hence, the mean difference of predicted and observed values is not significantly different from zero. Additionally, Pearson's correlation coefficient (0.7150, $p<0.01$) points to a strong positive linear correlation between y and $\hat{y}$. The average absolute error, however, is 4.58 US$ and *MAPE* is 81.66%. This corresponds to an absolute percentage error ranging between 0.71% and 1,478.79%. A comparison with the median absolute percentage error (32.93%) suggests that the large *MAPE* is driven by a few outliers.

Our analysis of the outliers reveals two insights. First, we obtain ten absolute percentage errors above 100%, eight of which correspond to WTP values that are related to an increasing share in biomass. The three absolute percentage errors greater than 200% correspond to WTP values that deviate from the mean WTP of the respective study by at least a factor of ten. The positive Spearman's correlation coefficient (0.2590, $p<0.05$) indicates that the meta-regression transfer function fails at estimating WTP for an increase in biomass. Second, another outlier is the WTP value provided by the Haneman et al. (2011) study for Spain. Their WTP question is linked to a whole emission mitigating policy program. It is, therefore, likely that they overestimate WTP for an increase in green electricity only.[4] Omitting these outliers reduces the predicted values by 22 observations.

[4] Their value is 8.6 times the average of all other studies for Spain (Gracia et al., 2012; Solino et al., 2009).

Investigating the quality of the value transfer based on the remaining 63 predicted WTP values from model 1 (full data set), the fit of the value transfer improves significantly; linear correlation increases (0.7966, p<0.01) and average absolute transfer error decreases (3.45 US$). *MAPE* more than halves to 36.28% and absolute percentage error now ranges between 0.71% and 178.40%. This improvement of average forecast performance, however, comes at the cost of an underestimation (p<0.05) of the observed mean WTP. When investigating the linear relationship of the observed WTP and the predicted WTP, however, we estimate $\alpha = -0.0192$ ($\alpha = 0$: t $= 0.22$) and $\beta = 1.0163$ ($\beta = 1$: t $= 0.13$) for the linear regression of *LN_WTP* on its prediction $\widehat{\ln(y)}$ (equation 2), and gain an R-squared of 0.8752.

When re-estimating model 1 (equation 1) with the restricted sample of 63 the regression coefficients are comparable to the results using the full data set (see above), but the R-squared increases for every function; this underlines the robustness of our meta-regression model. Additionally, mean difference in predicted and observed WTP is not significantly different from zero. Further, their positive linear correlation is now 0.8598 (p<0.01). Mean absolute error amounts to 2.89 US$ per household and month, and corresponds to a *MAPE* of 34.16% and an absolute percentage error ranging between 0.15% and 165.58%. This indicates that the restricted data set is more efficient in meta-regression function based value transfer than the full data set when analysing WTP per household and month. This is confirmed when investigating the linear relationship of the observed WTP and the predicted WTP; the constant term α is not significantly different from zero ($\alpha = 0.221$; p=0.147) and the coefficient β is not significantly different from 1 ($\beta = 0.9091; t = 2.61$), but the R-squared (0.8515) is slightly lower.

5.2.2. WTP per kilowatt-hour

Focusing on our other dependent variable, WTP per kilowatt-hour (model 2, full data set), there is no significant difference between predicted and observed values (t-statistic=0.7333). Pearson's correlation coefficient (0.6963, p<0.01) underlines a strong positive correlation between y and $\hat{y}$. Compared to above (Section 5.2.1, full data set), we calculate a higher *MAPE* (90.06%), and a lower median absolute percentage error (27.31%), corresponding to an absolute percentage error ranging between 0.22% and 1,475.42%. The mean absolute error is 1.02 US-Cents per kilowatt-hour.

If we exclude the outliers identified above, mean absolute error decreases (0.82 US-Cents). Median absolute percentage error (22.16%) and *MAPE* (42.92%), also, perform better. Overall, absolute percentage error ranges between 0.22% and 285.19%. When comparing these results to those above (Section 5.2.1, full data set) there is on average no significant difference between predicted and observed WTP.

When re-estimating the meta-regression transfer function based on the restricted data set (see Section 5.2.1) the results are not that different compared to above; mean absolute error (0.81 US-Cents) and *MAPE* (38.03%) decrease slightly and median absolute percentage error (26.66%) increases slightly (absolute percentage error ranging between 0.46% and 239.39%). Thus, WTP values describing an increase in biomass have not such an impact on value transfer for WTP per kilowatt-hour as compared to WTP per household and month.

6. Discussion / Conclusions

This article provides a comprehensive overview of the valuation literature on green electricity and has identified key characteristics that determine peoples' WTP for green electricity. In general, people are willing to pay for green electricity. People in Finland and the US express the largest WTPs per household and per month, while people in Chile, Italy and Germany have the highest WTP per kilowatt-hour. Countries with high electricity consumption per capita but low energy prices, such as the US and Finland, naturally state a higher WTP per household, but a low WTP per kilowatt-hour. However, WTP per kilowatt-hour is seldom reported in the literature. This could be because study participants may have a better overview of their monthly electricity expenditures than of the electricity price per kilowatt-hour.

Nevertheless, politicians lean on WTP values provided by researches so it is important to communicate WTP influencing factors, and to express WTP values in feasible units, e.g. a WTP per kilowatt-hour if politicians need advice choosing an optimal tax on electricity. That is why we recommend researches either to directly use the unit kilowatt-hour in stated preference WTP questions or to convert values per household and month by using information about household-size and electricity consumption.

Turning to the quantitative results of this article, our meta-regression shows that preferences for electricity generation differ by source. In contrast to other renewable energy sources, experiences with hydropower reduce acceptance of renewable energy probably because hydropower consumes more land and has a more significant environmental impact than other renewables. Furthermore, people who are informed on the type of power plant to be substituted by renewables, tend to exhibit a higher WTP. This gives evidence that acceptance of renewable energies strongly depends on informing people about concrete plans, alternatives and status quo.

Significance of the dummy variables, describing the exploratory variables of study's WTP estimation, suggests that controlling for knowledge about renewables, price, household characteristics, income and education significantly influences WTP estimates. Ignoring these attributes in future WTP estimations might result in biased coefficients. Our analysis gives evidence that significance of other exploratory variables is caused by characteristics which are related to a specific study site; that is, they might result in another effect direction, such as regional effects, which are not caused by the region itself, but its characteristics.

Similar, studies state inconclusive WTP values for an increase in biomass. It seems that the acceptance of this renewable energy facility depends on characteristics which are not covered by our meta-regression, such as land use change. For this reason, our value transfer for an increase in biomass fails. Nevertheless, we are able to predict the other WTP values with a median percentage error between 22% and 29% and a *MAPE* between 24% and 43%, depending on the underlying specification. These values are comparable to the transfer errors reported in other value transfer exercises (but not related to renewable energy; e.g. Brouwer, 2000). Further, the absolute errors of the value transfer are very small (about 3 US$ per household and month respectively 0.80 US-Cents per kilowatt-hour). Thus, these errors might be practically acceptable to use them for policy measures.

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