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Determinants of the price-premium for Green Energy: Evidence from an OECD cross-section*

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Abstract

Using data from a large, multi-country survey, this paper investigates the determinants of preferences for a completely green residential electricity system. Three important questions are addressed: (i) How much are households willing to pay to use only renewable energy? (ii) Does willingness-to-pay (wtp) vary significantly across household groups and countries? and (iii) What drives the decision to enter the (hypothetical) market for green energy and, given entry, what drives the level of wtp? The analysis here differs from previous ones in the literature in two distinct ways: first, data and analyses are comparable across countries and second, a comprehensive attempt to address censoring and heterogeneity is carried out. The survey data indicate, in common with prior analyses and market experience, a low wtp, about $9-10\%$. This study addressed a key aspect: how important is income for understanding wtp, relative to more "attitudinal" determinants? Surprisingly, income exerts almost no effect on wtp, at the margin; this result is robust to controlling for censoring and heterogeneity. Key determinants of the wtp decision appear to be environmental attitudes, particularly membership in an environmental organization.

Keywords: green electricity, willingness-to-pay, censoring, quantile regression, renewable energy

JEL classification: Q42, Q51, C24, C21

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1 Introduction

There is a substantial literature on the price premium (or willingness-to-pay, wtp) for green energy in the residential sector (Clark et al. (2003), Hansla et al. (2008), Kotchen & Moore (2007), Yoo & Kwak (2009) and Shi et al. (2013). This literature has added to our understanding of factors that influence the premium, as well to how large such a premium may be. The analysis is undertaken, in a large majority of cases, within a single country, often with rather small samples. By contrast, this paper uses a large-scale OECD survey consisting of about 12,000 observations on households in 11 OECD countries.

We examine three questions:

1. How much are households willing to pay to use only renewable energy?

2. Does willingness-to-pay (wtp) vary significantly across household groups and countries? Our focal point, however, is the next question

3. what drives the decision to enter the (hypothetical) market for green energy and, given entry, what drives the level of wtp?

We consider the decision to pay in a two-stage fashion; the consumer first decides if it is worthwhile "entering" the (hypothetical) market and then, given entry, how much to pay. These "entry" and "level" decisions, labelled "extensive" and "intensive" margins (e.g. Kotchen & Moore (2007)), are not necessarily driven by the same factors, a fact we exploit in the econometric modeling. Conventional methods (e.g. standard Tobit) typically used ignore important features of the conditional distribution and cannot accommodate unobserved or non-additive heterogeneity. The latter is a prominent feature in a diverse multi-country setting as here (see section 3.2 for details). We use a recently developed (Chernozhukov et al. (2011)) censored quantile regression (CQR) method to handle censoring and unobserved heterogeneity in a single framework. Given the well-known tendency of commonly used censored and binary regression models to be highly sensitive to heteroscedasticity, the CQR framework is an ideal choice when interpreted as a heteroscedasticity-robust censored regression framework [1].

[1] Quantile regressions were initially developed as a location-scale generalization of commonly used regression frame-

We apply this econometric framework to the OECD EPIC (Environmental Policy and Individual Choice) surveys. Residential energy demand is one of the five areas the EPIC survey covers, and it includes a scenario involving paying for converting the existing energy system (in a given country) to one based solely on renewables. This is unrealistic in the short run, but it remains the sustainable solution that many countries are aiming at. The scenario is necessarily hypothetical, which raises familiar issues about data quality. However, because many companies actually offer to sell "green electricity" at a price premium, the good itself is, typically, not unfamiliar to respondents. This reduces some of the usual problems encountered when using hypothetical scenarios in surveys (including, but not limited to, unfamiliarity with the good offered). More details on the survey is provided in section 4.1 below. The rest of the paper proceeds as follows: section 2 provides a compact update of the literature, section 3 explains our conceptual and empirical framework, while section 4 provides the main results. Section 5 summarizes our main results, and concludes with a few thoughts on price premia in the market for green electricity. The appendix compares properties of the estimators used in this paper.

2 Literature review

There is now a substantial literature on the value households place on an energy system based on renewable energy. Such information is potentially useful for policy-making, since it provides a benchmark for comparing the benefits and the costs of expanding renewable energy sources.

Table C.1 (Section C) provides a summary of some of the most recent empirical literature in the stated-preference setting, which we briefly summarize here. A detailed review of studies up to 2009 is provided in Shi et al. (2013); see also Kriström (2013) for an updated review. The literature now cover a substantial number of countries, including developed and developing countries, with two noteworthy points. First, researchers involved in this literature represent a fairly wide set of disciplines from various parts of the social sciences and second, the choice of statistical approach varies, but there is a preponderance of papers using the Logit- Tobit-type approaches.

We begin with the analysis in Oliver et al. (2011), one of the recent studies that brings in a developing country perspective. Employing a random sample of 543 households in the Cape Peninsula

works, which allowed only the location of the distribution to vary with covariates. See Koenker (2005) for more details on this interpretation.

(SA), this study usee correlation and logit models to test a number of hypotheses. A key finding is that income correlates positively with wtp. We return to this finding later, because income can affect the decision to enter the green energy market and how much to pay, in different ways. The analysis in Abdullah & Jeanty (2011), focused on the value Kenyans (in the Kisimu district) place on electricity connection in rural areas, finds that respondents place a higher value on grid connection services compared to a photovoltaic alternative, leading the authors to propose, inter alia, subsidies for electricity connections.

Zorić and Hrovatin (Zorić & Hrovatin (2012)), using a sample of 450 Slovenian households and econometric methods similar to some of those in our analysis, find that income is a significant driver of wtp. They find an average wtp–in terms of %age increase in monthly electric bill– of about 9%, (which is comparable to the one we present in our analysis), a result which may be driven by electricity subsidies in Slovenia. Interestingly, they find that income is positively related to the level of wtp, but is not significant for the participation decision, a result opposite to what we report.

Ertör-Akyazi et al (Ertör-Akyazı et al. (2012)) study preferences for nuclear and renewable energy in Turkey, using a sample of 2248 urban Turks. The logit model used shows that endorsement of renewable energy is positively related to education and environmental concern, while "economy-oriented" individuals were less likely to endorse renewable energy. Liu et al (Liu et al. (2012)) use a survey of respondents in Shandong and confirm the findings of several other studies, that income is positively related to wtp, as is knowledge; age however, has a negative impact.

Turning now to a few examples of recent studies from developed countries, we begin with the analysis in Gerpott & Mahmudova (2010). This study, using a survey of 238 German households, finds that roughly half the sample (53.5%) are "in-the-market" for "green energy", while 26.1% support a price premium in the range 5-10%. These figures are similar to what has been found in the EPIC surveys, as is the finding that attitudes towards the environment play a significant role in understanding wtp. Ozaki (Ozaki (2011)) asks a somewhat different question in her survey of 103 UK respondents; she looks at the switching, or adoption, decision from a sociology standpoint. She reports at least one surprising result, given that the sample had (according to the author) a "green bias":

> "... we found great hesitation among them [the respondents] about adopting a

> green electricity tariff, and even those with high adoption intentions are indecisive. Positive green attitudes towards pro-environmental behaviors do not necessarily translate into the performance of the behaviors. “ (p14)

The reasons why “green” consumers do not automatically/necessarily switch to “green” electricity include (as reported in Ozaki (2011)), switching costs (in general terms), uncertainty about the quality of green energy and the lack of strong social norms (for more on norms in this context Ek & Söderholm (2008, 2010)). The switching inconvenience respondents refer to in this study appears directly related to the “hidden costs” economists apply to explain tardiness in switching to more energy saving technology.

Hansla (2011) is a study based on psychological theories, employing a sample of 1800 Swedes (with a 26.5% response rate). Respondents were shown five different price premia and asked how likely they would be to make the switch (to green electricity) for each premium. This study provides some evidence for the idea that altruism positively affects the probability of paying the premium.

Zhai and Williams (Zhai & Williams (2012)) scrutinize adoption of photovoltaics (PV), using a survey of 487 homeowners in Phoenix (21 of who had already installed a grid connected PV system). The authors claim that it is not only direct economic consequences that are important determinants of adoption, but that maintenance and environmental awareness also play a role.

Soskin & Squires (2013) is a study analyzing the value household place on rooftop solar generation, using a sample of 25000 electricity users in Florida, USA. This study used a 4 by 4 split-sample design, involving 4 different solar programs (the fourth was a green pricing plan, used as a control group) and 4 different vectors of costs. A probit model was used to study factors influencing participation, ie ”agree to purchase or sign up for a solar program” . The study confirms the findings of earlier studies on green pricing, showing that income, education and attitudes play a role. Regarding investing in solar panels, it reports an interesting divide; older, low-income and anti-environmental individuals ”are unlikely to choose solar regardless of price”(p. 108), while the cost variable is significant in a population consisting of college graduates who buy environmentally friendly products. This potentially explains why the cost of solar is not significant in the adoption decision for the full sample.

Scarpa and Willis (Scarpa & Willis (2010)) study green energy adoption (solar and wind), using a choice experiment with 1279 UK respondents. In one set of experiments, targeting discretionary micro-generation adoption, they varied system (solar hot water, wind turbine and solar electricity), capital cost, maintenance cost and ”recommended by” (e.g. a friend, engineer). They replicate the oft-repeated finding that while households are willing-to-pay for renewable energy, this value does not cover the total (household) cost of switching. The very same conclusions are obtained in the study in Claudy et al. (2011), which uses double-bounded contingent valuation to analyze the wtp for different micro-generation technologies in a stratified Irish sample (N=1012) of home-owners.

As a final example of recent research in this area, we turn to the analysis in Strazzera et al. (2012). This CV study splits a sample of 358 individuals in the province of Oristano, Italy, into two sub-samples, each of which is asked about coal and solar power but with different ordering of coal and solar. This study attempted to elicit a) the (negative) value of coal b) the value of renewables. In the case of a switch to coal, the respondents would be offered a price which would reduce their utility bill (i.e. a discount on the current price). In the case of switching to renewables (that would entail receiving all electricity from solar energy), the respondent would pay a premium on the price, a scenario which they be free to reject. The average discount accepted is 64% of the annual bill for the switch to only coal, while the switch to only solar is valued at 40% surcharge on the existing bill.

If we compare these new contributions to the literature to the review in Kriström (2011), some of the conclusions made there are not challenged by new findings. These include the importance of environmental attitudes and income. Consistent with the findings reported below, a few of the most recent studies do report higher wtp estimates than found earlier in the EPIC survey. Market research demonstrates that the extractable price premium in this market is only a few percentage points; we found an average of about 4% in the previous survey, which has risen to almost 10% in this survey. Comparability issues (studies are using different elicitation mechanism, different scenarios etc) make it difficult to make much of this finding. Still, the valuations are somewhat higher in more recent studies.

3 Framework

3.1 Conceptual framework

We begin first by relating our conceptual framework to the received theory from revealed preference studies, which combine a theoretical model and its empirical implementation. This allows us to link the extensive and intensive margin decisions to recent theoretical advances and to derive specific implications of important variables, in particular income, for these entry and level decisions.

In our conceptual framework, individuals have an interest in contributing to a global public good (reduced GHG emissions), labelled G, via an added tariff, p_i^g, chosen by them, for all of their current electric consumption, Q_i, with the restriction that Q_i does not depend upon p_i^g[2]. Our payment resembles the Green Tariff Mechanism (GTM) of Kotchen & Moore (2007), with two important differences: first, individuals pay a self-selected tariff for all units of consumption and second, individuals are not allowed to alter consumption based on the green tariff. Their model provides an approximation of our set up[3], in terms of deriving predictions regarding impact of two categories of variables, *environmental affinity,* θ and income, m. In one of the GTMs considered, theory implies that increases in θ (corresponding to greater concern for the environment) leads to increased participation in the program, but increases in income *need not*. Their main empirical finding (using data on consumers from a specific utility in Tennessee) is that the decision on whether to contribute (the extensive margin) is not determined in the same way as the decision on how much to contribute (the intensive margin).

3.2 Econometric framework

Our analysis is complicated by two features of the data: censoring (wtp data are censored at 0) and (potentially) unobserved heterogeneity. There have been very few attempts at jointly addressing censoring and heterogeneity. Kowalski (2009), using the framework developed in Chernozhukov et al. (2011), unifies these features in an application. This approach makes it possible, for example,

[2] This means that the premium, p_i^g, is interpreted as the wtp for green energy (alternatively, the global public good, G).

[3] To see this, observe that our model is very similar to their GTM, with the consumer problem as in their equation (5), with $p_i := \pi\alpha_i$, and $p_i \geq 0$ and the optimization is over p_i, instead of α_i, with y_i fixed at the level with $p_i = 0$. This corresponds to none of their three models, the VCM, the GTM and the all-or-nothing GTM, with $\alpha_i \in \{0, 1\}$.

to obtain *elasticity* of income across the whole conditional distribution of wtp. In addition, unlike traditional two-part or hurdle models for censored data, it is not necessary to understand the "nature" of the zeros, since the Censored Quantile Regression (CQR) estimator is identical in all cases and censoring is handled non-parametrically. Finally, unobserved individual heterogeneity (or non-additive observed heterogeneity) is addressed as a part of the modeling framework. It might be useful to explain these empirical issues in some more detail and we begin with the case of censoring.

There are well known issues in dealing with censored (and truncated) data, in particular when 0 does not represent a "missing data" or "selection" interpretation[4]. There are two key issues: factors which influence non-zero choices, denoted $\mathbb{P}(y > 0|X)$, and, conditional on a non-zero choice, some features of the distribution $f(y|X)$or $F(y|X)$, typically the conditional mean $\mathbb{E}(y|X, y > 0)$. Popular methods are, in this context, typically highly parametric and suffer from drawbacks such as lack of robustness to heteroscedasticity[5]. In addition, when data are likely drawn from different countries and contexts, with country-specific factors only imperfectly captured, an important question that arises is of unobserved heterogeneity[6]. The QR framework accommodates heterogeneity along the unobserved dimension[7] (of the quantile). If data on individual level prices are missing here, and assuming that this is the only relevant variable missing, one can interpret e.g. the coefficient on income as income responsiveness at varying quantiles of the price distribution.

There have been a variety of approaches[8] to dealing with zero wtp[9]. The widely used Tobit

[4]The way the price premium question was posed actually imposes a right-hand upper limit as well, but we ignore it here, since there are very few observations close to the right-limit.

[5]Binary choice models and censored regression models, unlike linear regression frameworks, are not only inefficient but *inconsistent* under any kind of heterogeneity—the simplest case being heteroscedasticity– observed or not, an issue ignored in applied settings. This is because the functional form of $\mathbb{E}(y|X)$ is derived based on a particular distributional assumption, the homoscedastic normal distribution (Wooldridge (2010, Chapter 17, pp 685-6)).

[6]Typically, when eliciting wtp with the CV method, a random parameters approach is available for certain model frameworks to accommodate unobserved heterogeneity (eg. Carlsson & Martinsson (2004, 2009)). However, it is difficult to accommodate in this framework both censoring and unobserved heterogeneity, without imposing further parametric structure on the framework.

[7]It is straightforward to allow for heterogeneity along the *observed* dimensions by simply interacting the relevant dimension (e.g. income) with say urban residence; this approach has been applied for this dataset in a demand estimation context, in Krishnamurthy, C.K. & Kriström (2013), who interact country-dummies with the income coefficient. However, given the relatively complicated multi-equation estimation frameworks used, we do not pursue that approach here. Note however that in both the quantile regressions as well as the preferred model, the ET2T, due to the non-linear nature of the models, the model coefficients are actually country-specific (as in the case of the trans-log model in Krishnamurthy, C.K. & Kriström (2013)); we do not however emphasize these aspects here and report average marginal effects but note that it is possible to report instead country-specific average marginal effects.

[8]We do not cover the "spike"-like models, since they have typically been applied to dichotomous choice CV studies, rather than to the continuous-choice setting considered here. See e.g. Hanley et al. (2009) and references therein.

[9]There are at least two distinct reasons for "0" wtp (Yu & Abler (2010)): "protest zeros" (with the individuals feeling

models substantially restrict the scope for dependence between the "participation" decision and the "amount" decision (eg. Carlsson & Martinsson (2007)). In the revealed preference literature on green energy, these drawbacks have been noted (Kotchen & Moore (2007, §4.1)), and the empirical framework used has been essentially to split the decision framework into two parts: a probit for participation and a truncated regression for the amount.

The so-called two-part models or double-hurdle models are more general. Here, the first stage determines the "participation" decision and the second the "amount". These models are only marginally less restrictive than Tobit models, since the two decisions are essentially independent (see Goodwin et al. (1993) for e.g.). Jones (1989) focuses on generalizations of the double hurdle models, wherein dependence between the participation and amount decisions are allowed explicitly; such models have been relatively infrequently used in the wtp literature (e.g. Alvarez-Farizo (1999)). Finally, Yu & Abler (2010) provide a more general framework for computation of mean wtp, taking into account all types of 0's and missing values. Yet, their framework suffers from many drawbacks, including the sequential nature of the error process (in the absence of such assumptions, the parameters in any of the four stages are not even identified) as well as the rather ad-hoc computation of the standard errors on their estimates[10].

We provide results from four parametric regression frameworks: plain (biased) OLS, a simple Tobit, a slightly improved two-step model, the Truncated Normal Hurdle Model and finally, the so-called Exponential Type II Tobit (ET2T), our preferred censoring framework. The truncated normal "hurdle" differs from the Tobit model in allowing for a slightly more nuanced impact on participation probabilities[11] while maintaining the assumption of conditional independence. The ET2T is not based on the assumption of conditional independence between the participation and amount decisions. This is useful here, since both decisions are likely to have common unobserved factors, even after conditioning on presumptive determinants of both (see Section A for a comparison of

that they should not be paying extra for the good, for e.g., while having a possibly non-zero valuation of the good), and "true zeros" (in which respondents actually value the added benefits as zero). Our approach below assumes that the 0 wtp is a corner solution i.e. the individuals valued the benefit of the global public good as not contributing to their utility.

[10]In addition, it is not clear how individual heterogeneity can be accommodated since random coefficient approaches are likely infeasible in this set up (by virtue of identifiability).

[11]Recall that, in Tobit models, two undesirable features follow from the assumptions: the ratio of participation probabilities from two continuous variables has the same sign as that of $\mathbb{E}(WTP|X, WTP > 0)$, and the marginal effects of any variable has the same sign in the "participation" and "amount" equations. In the case of the normal truncated regression model above, both these undesirable features disappear.

both models). In fact, this model is a slight modification of the familiar *heckman selection model* (also called the "Type II Tobit" model, abbreviated T2T), with the variable of interest in the "outcome" equation being in log form (hence, *exponential* T2T). Because of its flexibility in allowing for a variety of interesting effects, this is our preferred model[12].

Typically, when more than one observation per individual is available, as in Carlsson & Martinsson (2007, 2008), a random parameter approach is used, which is a rather restrictive[13]. Other approaches, including taking into account characteristics of alternatives (eg. in transport modelling; see Amador et al. (2005)), are not available in this instance, since there is no simple "substitute" for the global environmental good (reduction in GHG's) that the shift envisaged here entails.

The Quantile Regression framework, in this case, provides a natural way to accommodate unobserved heterogeneity[14]. For instance, the effect on an additional unit of income is allowed to vary across the distribution of wtp. This can accommodate scenarios wherein income exerts a substantially different impact at different regions of the conditional distribution of wtp.

We provide here a brief idea of how the CQR estimator works, and refer to Chernozhukov et al. (2011) or Kowalski (2009) for more technical details, and to Chernozhukov et al. (2012) for its stata implementation. Two essential elements motivate the CQR approach; first, similar to the mean regression, censoring induces a bias in coefficients at all quantiles in this case[15]. Second, direct application of the "max" operator renders the otherwise convex problem non-convex and significantly increases the computational burden. Therefore Chernozhukov et al. (2011) use the following three-step idea: first, a fraction of the observations most likely to be uncensored (based upon a probit or logit) are retained and are used, in a second step, for a normal QR. Finally, based on predicted values from this regression, a larger set of observations are retained for yet another QR. We report average marginal effect, $\frac{\partial Q_\tau(wtp|X)}{\partial X_j}$, for each covariate X_j, where $Q_\tau(wtp|X)$ stands

[12] As with the selection model, identification is tricky with the same covariates appearing in both the participation and amount decision; we therefore exclude two variables, marital and employment status, from the participation equation.

[13] Both due to the specific assumptions of normality which underlie these models, as well as the lack of extensions to the first stage or participation decision-see footnote 5.

[14] There is an immense literature on QR in applied economics today (Abrevaya & Dahl (2008); Arias et al. (2001); Chernozhukov & Hansen (2006); Fattouh et al. (2005); Kowalski (2009); Trofimenko (2008), among others), with a textbook treatment in Koenker (2005).

[15] Unlike the mean case, uncensored conditional quantiles are in principle easily recovered, since max (Quantile) is the same as the Quantile(max), a property not shared by the mean. In other words, quantiles are equivariant to monotone transformations i.e.$Q_{h(Y)} = h(Q(Y))$ whenever h is a monotonic function, such as $h = \max$. The same is not true of the expectation operator, $\mathbb{E}(h(Y)) \neq h(\mathbb{E}(Y))$ for arbitrary h, monotonic or not.

for the τ-th conditional (on X) quantile of wtp, since as with all censored regressions, the coefficient in the regression does not account for the impact of censoring[16].

We finally note that the only application of QR in a wtp context that we note is in O'Garra & Mourato (2007), who evaluate the wtp (using a CV study) for introduction of hydrogen buses in London. Interestingly, they discard observations with zero wtp, a much smaller issue in their sample than in ours.

4 Analysis

We turn now to understanding pertinent drivers of wtp for green energy, and attempt to answer, in particular, the three questions posed earlier, repeated here for convenience: How much are households willing to pay to use only renewable energy? Does wtp vary significantly across household groups and countries? Finally, what drives the decision to enter the (hypothetical) market for green energy and, given entry, what drives the level of wtp? Before going into the econometric results, we explain important details of the survey we used and then provide key summary statistics of the data used.

4.1 The EPIC *survey*

Data for the analysis were drawn from the OECD's project on *Greening Household Behaviour*, as part of which a periodic survey on Environmental Policy and Individual Behaviour Change (EPIC), covering a number of countries and areas, is carried out. The second survey was conducted in 2011, and included 11 countries: Australia, Canada, Chile, France, Israel, Korea, Japan, the Netherlands, Spain, Sweden and Switzerland. We provide a very brief description of the survey, and refer to OECD (2013, Annex B) for survey details. About 1000 individuals in each country were surveyed using an internet-based questionnaire, for a total sample size of 12,200 households. The questionnaire collected information regarding household behaviours in five distinct areas (apart from household characteristics and environmental attitudes): residential energy use, waste generation and recycling, food consumption, personal transport, and water consumption. The present analy-

[16]We emphasise that, in the case of the CQR we use, the "two-stage" interpretation of the existing conditional mean models are not essential for estimation, since censoring is directly modeled in a quantile framework. In other words, in order to estimate consistently the impacts on different quantiles of the (conditional) wtp distribution, it is not necessary to have an interpretation of the "censoring" process.

sis uses data from the energy section. Sample selection followed a strategy of stratification based on income, age-group, region and gender. In order to account for sampling-related issues, ex-post probability weights were provided, which may be used to render estimation results using this sample comparable to those using random samples from country-level population distributions.

To address the thorny problem of comparing different currencies, the price premium question was phrased in terms of percentage of the existing bill. Furthermore, the individual is asked to consider the value of "re-mixing" current electricity consumption, such that the same number of Kwh as currently consumed is guaranteed to come from renewable sources only. In this way, we know that the value the individual places on this scenario is only related to the new mix and not to how many Kwh is consumed; this is in contrast to most studies in this literature.

4.2 Variable description and summary statistics

The price premium question asked respondents about their wtp for a completely green energy system, in terms of percentage of current electricity bill (annual), with individuals allowed to choose any continuous amount between 0 and 100%. The usable responses to this question were 9667. Only 8829 observations were usable in the regressions, due to missing values on other variables, primarily income[17] . Tables (1) and (2) provide summary statistics for the variables used in the regression.

A large part of the literature postulates income as an important determinant of wtp, both for the intensive and extensive margins (Kotchen & Moore (2007), for instance). However, it is not evident what is the appropriate measure of income to use here; for instance, Kotchen & Moore (2007) (and, in a different context, Kotchen & Moore (2008)), use members in a household as a measure of disposable income, mostly since income is a missing variable. Given that we do have income as a variable, we use both in order to capture different aspects of household characteristics, with a strong prior expectation that larger values correspond to lower disposable income and are likely associated with higher participation and amount (see also footnote 22).

As noted above, several papers in this literature find non-economic attributes, such as attitudes

[17] No particular data cleaning exercises were carried out. The only concern corresponded to income with a possibility for very high and low income households to substantially differ. Winsorizing the income variable at both high and low income (the upper and lower 5%), however, provides results (not reported) broadly similar.

to the environment, an important determinant of wtp. The EPIC survey provides a large collection of self-reported variables pertaining to distinct environment-related behaviors/attributes; of these, we choose the following two as being most relevant to our purpose: self-reported membership in an environmental organization (following Kotchen & Moore (2008)) and an index derived from measures taken to save energy. Following Kotchen & Moore (2008), we expect membership to have a positive effect; however, we are agnostic about (and theory provides little guidance regarding) whether the impact is on the participation or the amount decision. Our prior on the other indicator is very similar. Evidence on the importance of other common household characteristics are mixed in the literature, see table C.1.

Country	mean	sd	Obs. I	Obs. II
Australia	10.81	17.99	721	280
Canada	11.87	19.03	713	263
Chile	18.39	21.72	737	165
France	9.64	16.31	869	368
Israel	15.03	21.85	764	252
Japan	10.33	15.81	725	336
Korea	17.96	19.34	800	173
Netherlands	7.76	13.82	643	276
Spain	10.54	17.49	755	318
Sweden	10.22	16.61	709	262
Switzerland	13.42	16.16	793	204
Total	12.55	18.35	8229	2897

Notes: Obs. I is the total number of non-missing observations while Obs. II is the number of observations in Obs. I which have 0 wtp.

Table 2: Summary statistics for wtp (as % of current electricity bill).

4.3 Extensive and intensive margin decisions

We begin with analysing the impact of two variable classes, income and environmental affinity. Since the coefficients do not convey the full effect of a variable on each decision, we present the results in the form of Average Marginal Effects (AME's) i.e. marginal effect for each variable computed at all observed values of the dependent variables, and then averaged, with standard errors computed as detailed below. Note that for the ET2T model, the coefficients on the dummy variables can be interpreted as proportional effects (see Krishnamurthy, C.K. & Kriström (2013, footnote 13,

	Australia	Canada	Chile	France	Israel	Japan	Korea	Netherlands	Spain	Sweden	Switzerland	Total
Income (in euro)	49179.0	44243.2	14026.5	38767.7	26753.1	49716.0	28202.9	39719.1	29646.1	42137.0	62888.7	38612.7
	(27473.6)	(27113.5)	(10512.1)	(17885.1)	(15363.6)	(29220.8)	(13995.5)	(16942.1)	(16449.1)	(19003.4)	(29881.7)	(24900.4)
Mem. of Envt. Org. (1=Yes)	0.103	0.111	0.193	0.0990	0.132	0.0372	0.0650	0.138	0.114	0.124	0.223	0.122
	(0.304)	(0.314)	(0.395)	(0.299)	(0.339)	(0.189)	(0.247)	(0.346)	(0.318)	(0.330)	(0.417)	(0.327)
Energy Behaviour Index	7.953	7.107	8.301	7.962	7.593	7.090	7.759	6.982	8.304	5.497	6.851	7.422
	(1.628)	(1.762)	(1.629)	(1.613)	(1.626)	(1.823)	(1.682)	(1.706)	(1.487)	(1.826)	(1.773)	(1.854)
Members under 18	0.692	0.505	0.882	0.670	1.068	0.451	0.751	0.594	0.607	0.553	0.575	0.671
	(1.031)	(0.900)	(1.006)	(0.980)	(1.262)	(0.809)	(0.860)	(0.969)	(0.891)	(0.920)	(0.922)	(0.981)
Length of stay at residence(years)	2.313	2.509	2.607	2.613	2.657	2.913	2.450	2.829	2.813	2.495	2.638	2.619
	(1.073)	(1.091)	(1.087)	(1.095)	(1.093)	(1.024)	(0.994)	(1.022)	(1.006)	(1.085)	(1.052)	(1.070)
Home Type(1=Multi-dwelling)	0.146	0.276	0.216	0.389	0.669	0.403	0.703	0.218	0.735	0.520	0.647	0.455
	(0.353)	(0.447)	(0.412)	(0.488)	(0.471)	(0.491)	(0.457)	(0.413)	(0.442)	(0.500)	(0.478)	(0.498)
Urban (1=Yes)	0.252	0.446	0.730	0.241	0.692	0.350	0.723	0.286	0.461	0.310	0.224	0.430
	(0.435)	(0.497)	(0.444)	(0.428)	(0.462)	(0.477)	(0.448)	(0.452)	(0.499)	(0.463)	(0.417)	(0.495)
Age of respondent (years)	41.97	43.38	37.00	43.24	38.37	43.28	38.78	45.79	41.35	43.87	44.82	41.93
	(13.91)	(13.82)	(12.14)	(13.93)	(12.96)	(13.24)	(11.39)	(13.05)	(12.94)	(14.33)	(14.15)	(13.54)
Years of post-school education	2.945	3.004	4.163	2.610	3.649	3.931	3.333	3.980	3.564	2.434	2.696	3.283
	(2.581)	(2.337)	(2.352)	(2.157)	(2.556)	(2.722)	(2.122)	(2.396)	(2.391)	(2.230)	(2.386)	(2.451)
Sex (1=Male)	0.528	0.530	0.525	0.537	0.491	0.526	0.531	0.594	0.547	0.570	0.509	0.534
	(0.500)	(0.499)	(0.500)	(0.499)	(0.500)	(0.500)	(0.499)	(0.491)	(0.498)	(0.495)	(0.500)	(0.499)
Married/Staying together (1=Yes)	0.632	0.630	0.540	0.759	0.673	0.603	0.640	0.764	0.679	0.646	0.631	0.655
	(0.482)	(0.483)	(0.499)	(0.428)	(0.470)	(0.490)	(0.480)	(0.425)	(0.467)	(0.479)	(0.483)	(0.475)
Employment (1=Employed)	0.589	0.600	0.704	0.651	0.751	0.663	0.701	0.686	0.624	0.647	0.660	0.662
	(0.492)	(0.490)	(0.457)	(0.477)	(0.433)	(0.473)	(0.458)	(0.465)	(0.485)	(0.478)	(0.474)	(0.473)
Observations	721	713	737	869	764	725	800	643	755	709	793	8229

Notes: Mean with s.d. in parentheses. For dummy variables, mean value is interpreted as the proportion of 1's in the sample.

Table 1: Summary statistics of dependent variables for the regression sample.

pp 24) for more details).

Standard error computation and inference for non-linear, likelihood-based models with non-random sampling is more involved than in the linear case, and we detail below how we compute the standard errors and associated test statistics. Standard error computations for all censored models used here account for the sampling structure, by clustering at the country-level. In addition, for the computation of the Average Marginal Effects (AME's), the non-random sampling of the data is accounted for by using a linearized variance estimator, instead of the usual delta-method based one. Given that there are no robust goodness-of-fit measures for many of the models used here, we provide instead an idea of model adequacy via the Wald test. In particular, we provide F- or χ^2-statistic for a test of all coefficients except the fixed effects and intercept in the full model. We use the this approach since the more conventional likelihood-based methods, such as the LR test, are not available in a setting where sampling is non-random, in particular where probability weights are used.

Results for the intensive margin ("amount" decision) for different models are reported in table 3 while those for the extensive margin ("participation" decision) are reported in table 4[18]. The effect of income is relatively uniform, across both the intensive and extensive margins[19]. Specifically, income is never significant for the intensive margin decision (row I, table 3), and has an unexpected sign in two of the censored models. The sign is positive for the extensive margin (row I, table 4), but insignificant. While some of the literature on eliciting wtp using CV-like studies do report the lack of significance of income, we believe that ours is the first study to report lack of significance of income to both margins, intensive and extensive. Kotchen & Moore (2007), for instance, report income as being significant in the extensive margin decision. Jacobsen et al. (2012) report a negative (but significant) coefficient on income for the intensive margin, and a positive (but insignificant) impact on the extensive margin. We return to an interpretation of the lack of significance of the income variable below. Shi et al. (2013) use the 2007 version of the EPIC survey, which is based on a different sample of OECD-countries, but the price premium question is (virtually) identical. They

[18]Note that since there is no particular theoretical reason–except for the ET2T model (see below)–to postulate that the presumptive determinants of the participation and amount decisions are different, the same variable sets appear in both equations.

[19]Unlike in Kotchen & Moore (2007), for our preferred censored model, the ET2T, both decisions are linked and it is not possible to decompose the regression into two independent ones. Therefore, it is not possible to compare the "joint" decision to the two constituent decisions.

find that income determines the entry decision, but plays no significant role for the level decision.

For environmental affinity, as indicated earlier, we use two variables: (self-reported) membership in an environmental organization and a measure of energy saving behaviour, the energy behaviour index. For the intensive margin decision (table 3), we note that the coefficient on membership is positive and significant and is remarkably similar in magnitude across comparable methods[20]; for instance, the difference in wtp between a member and non-member in the ET2T model is in the order of 1.4% of current electricity bill, on average. A similar result holds for the extensive margin, in table 4; members are, on average, 13% more likely to report positive wtp, based on the ET2T model, and the magnitudes of the effect is remarkably similar across all methods.

The variable energy behaviour index, constructed from individual reported energy saving behaviours, is an energy-specific measure of household behaviour; we find that an increase in the index is associated with a 0.8% increase in wtp[21], for the intensive margin. However, there is no significant impact and, if anything, participation is reduced (almost with the same magnitude) with increases in the index. This suggests that energy conservation behaviour does not directly correlate with proclivity for the global public good, conditional on other presumptive determinants.

We interpret the variable "number of individuals under 18" (the number of non-working individuals in the household) as being inversely related to disposable income; this variable is never significant for both decisions. For the intensive margin, the sign of this variable is contrary to our intuition. It positively affects the amount decision, but has a plausible negative impact on participation. The latter effect is also reported in the empirical section in Kotchen & Moore (2007), although they use the total size of the household[22]. In most models, age is negatively related to both the amount (significant) and participation decision (not significant), which is consistent with most other

[20] Recall the dependent variable in the ET2T variable is $\log(wtp)$; as a result, the magnitude of coefficients and marginal effects on the variables in that method is not comparable to those in the other methods–at least for the intensive margin–which use wtp in level as dependent variable.

[21] This is a rather approximate statement; formally, the index is a variable restricted to lie between 0 and 10, and in our estimation, we essentially consider this a continuous variable, leading to difficulties in interpretation. However, we believe that the interpretation as a continuous variable for the marginal effects is unlikely to be substantially misleading, especially for individuals not very close to either of the end points, 0 and 10, which is the vast majority of the individuals in the sample.

[22] Kotchen & Moore (2007) interpret household size as a measure decreasing in disposable income; however, with this variable, such an interpretation is confounded by the possibility of two working individuals in larger households. This is illustrated in our case by the *positive* coefficient on the total household size in both regressions when used instead of the number of individuals under 18 (results not reported). A better measure is non-income-earning size of the household, which we define to be the total number of individuals in the household who are under 18.

empirical studies. Education is likely to both increase participation probability and conditional on participation, the amount the individual is willing to pay, in keeping with most other studies.

Finally, gender is never seen to substantially affect either the intensive or the extensive margin which is consistent with previous empirical findings (e.g. Kotchen & Moore (2007)), while some of the literature focused specifically on charitable giving finds clear support for women being more likely to participate (i.e. find a negative sign on the coefficient on gender in the extensive margin). Given the substantial difficulties in comparing between varying sample sizes and characteristics across studies, it is difficult to make much of this finding. We do not detect any significant rural-urban divide; nor do we detect significant differences between those who live in apartments and those in isolated dwellings[23].

We turn now to interpreting two variables which have an income interpretation: income and number of individuals under 18 in the household. We interpret reported income as a measure of a variety of factors which are related to life-style, while the variable "number of under-18 individuals" is interpreted as inversely related to a discretionary part of income, with higher numbers corresponding to lower income. Alternative specifications, including using per-capita income, yielded similar results, with the income variable not significant.

To summarize, we find that income is not a significant determinant of either participation in the "green energy" market (the extensive margin) or on the amount decision (intensive margin). In particular, attitudinal factors such as membership of environmental organization and individual-specific factors, proxied by age and years of education, are more important determinants of the amount of wtp. In particular, in our preferred model, we find that the income elasticity of wtp is insignificant.

[23]Employment appears not to affect either participation or amount of wtp, conditional on other characteristics, while marital status-which, like employment, is intended to capture some aspects of feeling of "stability" of circumstances-strangely shows a negative coefficient in certain specifications, especially in the tobit model for the intensive margin (although not in our preferred specification). We conjecture that this effect is likely related to the positive significant coefficient on the number of under-18 individuals (also in the tobit model) in that couples staying together have a higher likelihood of having more children.

	OLS	**Tobit**	**TNH**	**ET2T**
log(house hold income)	-0.398	0.876	-0.370	0.041
	(-0.208)	(0.567)	(-0.207)	(0.474)
Member of Envt. Organisation	6.192***	5.903***	5.117***	0.337***
	(8.263)	(11.447)	(10.722)	(6.195)
Energy Behaviour Index	0.073	-0.173	0.083	0.008*
	(0.623)	(-0.655)	(0.728)	(1.763)
Members under 18	0.236	0.561***	0.270	0.021
	(0.675)	(3.197)	(0.763)	(1.597)
Length of stay at residence(years)	0.287	-0.343	0.261	0.011
	(0.840)	(-1.166)	(0.708)	(0.569)
Home Type(1=Multi-dwelling)	0.582	0.895**	0.467	0.034
	(0.600)	(2.412)	(0.474)	(0.695)
Urban(1=Yes)	0.043	0.197	0.159	-0.018
	(0.049)	(0.315)	(0.187)	(-0.312)
Age of respondent	-0.167***	-0.053	-0.182***	-0.009***
	(-5.795)	(-1.519)	(-6.482)	(-5.123)
Years of Post-Secondary Education	0.319*	0.466***	0.335*	0.019**
	(1.875)	(4.241)	(1.878)	(2.500)
Gender(1=Male)	0.424	0.421	0.353	-0.006
	(0.678)	(1.620)	(0.588)	(-0.269)
Marital Status(1=Married/staying together)	1.105	-0.946**	1.347*	0.040
	(1.522)	(-2.337)	(1.667)	(0.845)
Employment Status(1=Employed)	1.388	-0.083	1.713	0.039
	(1.108)	(-0.074)	(1.345)	(0.608)
Observations	5332	8229	5332	8229
Model Comparison Statistic		234.6	337.6	777.5

Notes: T-statistics in parentheses. The number of observations differ by method, with all two-step estimators using more observations, depending upon included covariates. All regressions include country-fixed effects (not reported) and use probability weights to account for sampling. Standard errors on marginal effects account for clustered survey design (see text for detailed description). The covariates in the regressions above are (i) OLS, Tobit and Double-hurdle: non-zero and non-missing observations (ii) ET2T: on all non-zero and non-missing observations in the amount equation. Model Comparison Statistic is the wald test statistic for joint significance of all coefficients excluding the country-fixed effects. $*$, $**$ and $***$ indicate significance at levels of respectively $p < 0.1$, $p < 0.05$ and $p < 0.01$.

Table 3: Average Marginal Effects for the conditional mean, $\dfrac{\partial \mathbb{E}\left(wtp|X, wtp > 0\right)}{\partial X_j}$, of wtp.

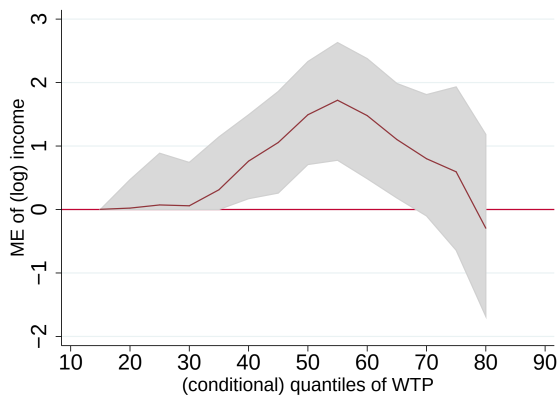
	Tobit	**Truncated Normal Hurdle**	**ET2T**
log(house hold income)	0.047	0.065*	0.044
	(1.029)	(1.713)	(1.476)
Member of Envt. Organisation	0.167***	0.145***	0.138***
	(7.679)	(5.396)	(6.712)
Energy Behaviour Index	-0.004	-0.009	-0.009
	(-0.624)	(-0.892)	(-0.913)
Members under 18	0.004	0.004	-0.003
	(0.380)	(0.259)	(-0.296)
Length of stay at residence(years)	-0.003	-0.012	-0.007
	(-0.402)	(-0.827)	(-0.592)
Home Type(1=Multi-dwelling)	0.001	0.006	0.000
	(0.063)	(0.351)	(0.024)
Urban(1=Yes)	-0.000	0.006	0.005
	(-0.016)	(0.390)	(0.301)
Age of respondent	-0.002*	0.000	-0.001
	(-1.909)	(0.019)	(-0.723)
Years of Post-Secondary Education	0.012***	0.012***	0.012***
	(3.387)	(4.114)	(4.015)
Gender(1=Male)	0.010	0.005	-0.000
	(1.338)	(0.275)	(-0.013)
Marital Status(1=Married/staying together)	-0.010	-0.042**	
	(-0.875)	(-1.979)	
Employment Status(1=Employed)	-0.014	-0.032	
	(-0.412)	(-1.119)	
Observations	8229	8229	8229
Model Comparison Statistic		383.1	

Notes: T-statistics in parentheses. For binary variables, the effects are the differences between the two categories of the independent variable. The Hurdle model has a first stage independent probit, and so the effects are those from a simple probit, with dependent variable $\mathbb{I}(wtp > 0)$. The Model Comparison Test Statistic thus pertains to a probit. The ET2T and Tobit are two-stage models; thus, the number of observations, as well as the Model Comparison Statistics, are the same as those for the marginal effects of the conditional mean. All regressions include country-fixed effects (not reported) and use probability weights to account for survey sampling. Standard error computations are identical to that in table 3. $*$, $**$ and $***$ indicate significance at levels of respectively $p < 0.1$, $p < 0.05$ and $p < 0.01$.

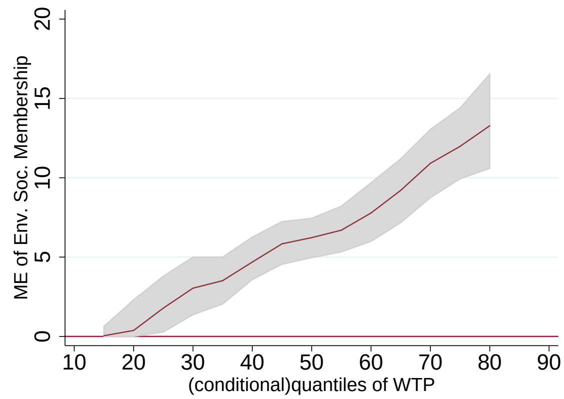
Table 4: Average Marginal Effects for conditional probability of participation, $\dfrac{\partial \mathbb{P}(wtp > 0|X)}{\partial X_j}$.

4.4 Unobserved heterogeneity

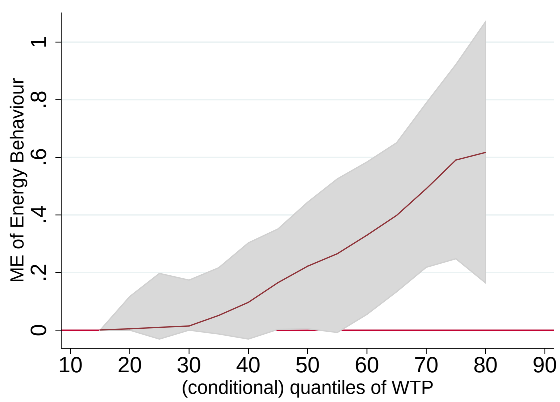
Does the QR provide a different characterisation of the relationships? We present the results in the form of a graph, a convenient and widely used way for visualizing the variation in coefficients (or effects) across a range of quantiles. Theory typically provides little guidance for which, and how many, quantiles to estimate; in empirical studies therefore, a wide range of quantiles are estimated, a practice which we follow by estimating (independent of each other) a range of conditional quantiles,



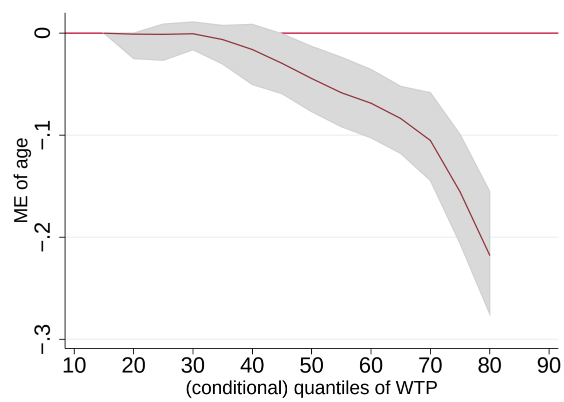
(a) ME for Income



(b) ME for envt. org. membership



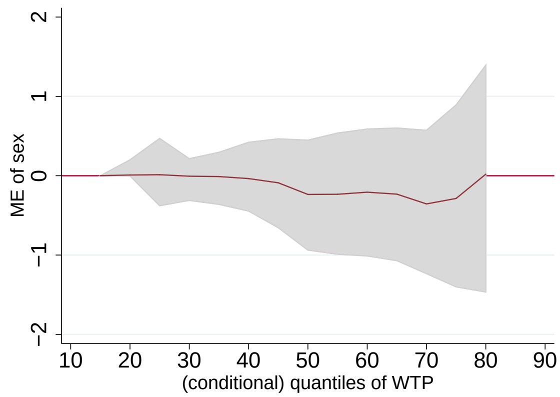
(c) ME for energy behaviour



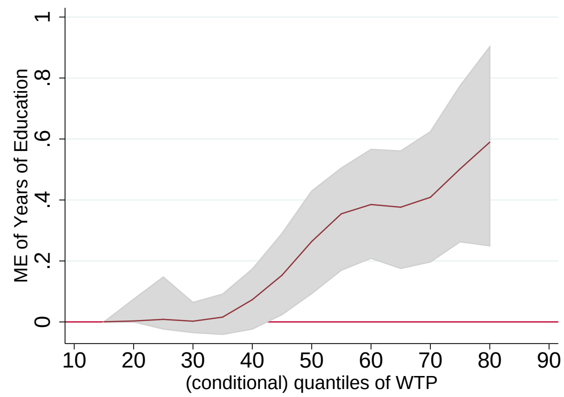
(d) ME for age

Figure 1: Average marginal effects from Censored QR for indicated variables

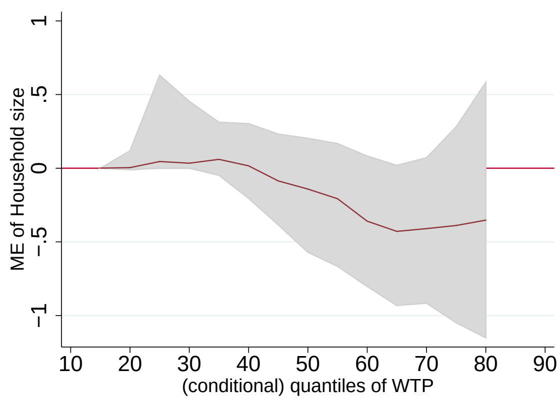
Notes: Average marginal effects and confidence intervals are independently estimated over a range of quantiles (estimated independently over a grid of quantiles, from the 25th to 90th, with increments of 5), from 500 independent resamples using the paired, weighted bootstrap. These estimates are then connected by a curve. Estimation at each quantile included country-specific fixed effects, and estimation (and resampling) procedure used probability weights to account for sampling. The gray region is the confidence region while the red coloured lines are the estimated coefficients; thus, confidence regions which do not overlap the zero line are to be considered "significant".



(a) ME for Gender



(b) ME for education



(c) ME for individuals under 18

Figure 2: Average marginal effects from CQR for indicated variables.

Notes: Average marginal effects and (bootstrap) confidence intervals, independently estimated over a range of quantiles; estimation, graphing and confidence interval computations are identical to those in fig. 1.

from the 25th percentile to the 90th, with increments of 5 percentiles, which are then plotted[24].

The key question of interest is the direction of effects obtained using the framework, compared to those using the conditional mean and participation probability models earlier used. The results are, however, not directly comparable since the modeling frameworks are rather different, especially in the censored regression case. Confidence intervals are computed, at each quantile and for each coefficient, using the weighted version of the paired bootstrap (see Section B for a few details regarding inference), with independent–across countries–sampling (conditional on the weights) assumed.

We now turn to interpreting the estimated effects, recalling first that the conditional mean estimates indicated income had an insignificant effect on both the amount and participation decisions, but was mostly of the correct sign, and significant in at least one model, in the participation decision. Income, in the QR setting (fig. 1), is positive throughout the range of quantiles estimated, but almost never significant. Thus, the quantile and two-stage models provide a similar picture, of a marginally or rarely significant income effect on wtp. A similar result is obtained for our preferred measure of disposable income, number of individuals under-18, whose estimated marginal effect is almost always zero. The implication is that neither the level of income nor disposable income play a substantial part in determining wtp (as defined here).

On the other hand, membership is not only positively related to wtp, but the impact of this indicator is seen to increase with the level of (conditional) wtp. In other words, conditional on other factors, the (marginal) impact of membership is larger among individuals with a higher wtp, with a probable "flattening out" around the 80th percentile. This is consistent with an economic interpretation of saturation in wtp beyond a certain level of existing wtp (as well as a reflection of the upper truncation of (unconditional) wtp at 100% of current electric bill). Energy behavior, another proxy for "responsible behavior" is never significant. While gender never exerts a significant impact on wtp–except perhaps at the tails wherein there are relatively few observations–, education does exert a positive impact, one which appears to be relatively "flat" across quantiles, indicating very similar effect at all quantiles. The effect of age is negative, with an increase in the magnitude

[24]There were issues with estimation of quantiles below the 20th, particularly between the 10th and 20th as a result of which, we report results only from the 25th. Also, with a relatively small, for quantile regression, sample size (of less than 9000), estimation far into the tails is typically fraught with uncertainty, as a result of which we do not proceed beyond the 90th percentile.

of the effect across the quantiles of wtp. This is consistent with the hypothesis that, conditional on other relevant factors, older individuals have a lower wtp.

In summary, results from the CQR framework indicate that: income is rarely a significant factor in understanding wtp decisions, age is negatively related, with an increasing magnitude of effect over the distribution of wtp (i.e. exerts a larger negative impact on higher levels of wtp than on lower), membership in an envt. Organization is a strongly positive determinant of wtp, whose impact is increasing across wtp quantiles (i.e. the effects of membership are more pronounced for those who have a higher wtp, similar to age) while education is marginally positively related to wtp, with similar impact across the quantiles. For most variables of interest, the effects from both frameworks used are of the same sign; the QR framework helps uncover, in addition, a pattern wherein individuals with high and low "inherent wtp" exhibit quantitatively different behavior as regards their observed characteristics. This pattern of behavior which is completely missed by the conditional-mean censored regression models.

In essence, this framework shows that only individuals with a high (conditional) wtp[25], corresponding roughly to the median and beyond, exhibit most of the behaviour uncovered in the regressions–since this is the region wherein most coefficients tend to be significant.

5 Conclusions

This paper uses the second round of the OECD cross-country EPIC survey, to shed some new light on residential demand for "green energy". The first round of EPIC data, from 2007, which uses a different set of countries, but with a very similar price premium question, were analyzed in Shi et al. (2013). Taken together, across a total set of 17 countries and more than 18,000 households interviewed, there are some common themes. In particular, and like the single-country studies, the EPIC surveys suggest that the price premium is small; it is difficult for firms to extract a significant premium and these sentiments are replicated in the hypothetical scenario used in the EPIC surveys .

[25]It is important to note that the conditional–on whatever regressors have been used–wtp can differ substantially from the unconditional (raw) wtp figures. In a typical linear QR model, one can easily obtain the conditional quantiles as predicted values of wtp at different quantiles and, using this as the estimated conditional distribution, draw wtp-values (for different values of the conditioning covariates) or even draw a sample from the conditional distribution and obtain the mean wtp, for a comparison with the raw. We do not have access to this mode of comparison due to the complications introduced by censoring. Essentially, obtaining "predicted values" at different quantiles are a complicated exercise and one which we do not undertake here. See also Section B.

A key contribution of this paper centers around analysis of decisions on the extensive and intensive margin, using recent econometric methods to test a number of predictions from economic theory. Theory suggests that income may play a role for these margins, but need not. Using four different econometric frameworks in the Tobit tradition, we are unable to demonstrate any strong link between income at either margin. Environmental affinity, proxied by (self-reported) membership in an environmental organization and a energy behaviour index, is expected to be positively related to either the extensive margin or to both margins. For the amount decision, the coefficient on membership is positive and significant, and remarkably similar across comparable methods. The difference between a member and non-member's wtp in our preferred model is in the order of 1.4% of current electricity bill; members are, on average, 13% more likely to report positive wtp. We do not detect any significant rural-urban divide, nor do we detect significant differences between those who live in apartments and those in isolated dwellings [26].

The quantile regression framework we use provides a natural way to accommodate unobserved heterogeneity, which we expect to be significant in a cross-country survey. We obtain essentially the same results as the Tobit-style models when it comes to the effect of income. For membership we get some additional insights regarding its effect; the (marginal) impact of membership is larger among individuals with a higher wtp, with a probable "flattening out", or saturation, around the 80th percentile. Education does exert a positive impact, which seems to be very similar effect at all quantiles. The effect of age is negative and increases across quantiles; conditional on other relevant factors, older individuals have a lower wtp.

We conclude with one general, and one specific, observation. The literature on "green energy" demand is now quite substantial and the price premium estimated can be compared with the substantial resources now being invested in "greening" the energy systems. Studies using the EPIC data are not intended to be part of a detailed cost-benefit analysis, yet if we weigh in the results from the current literature, it is possible to obtain some useful insights regarding the cost-benefit ratios. There are a significant number of reasons as to why data quality is hampered by hypothetical questions, but here we have a link to existing markets. If both the markets and the surveys point

[26] A separate analysis of Sweden carried out within the OECD-project by one of the authors of this paper, obtains some indication of a rural-urban divide. In particular, there is a difference between urbanites living in small apartments and those who live in isolated dwellings in the countryside of the north. The econometric framework used is different form the one we use here

to a low price premium, it is quite possible that the consumers are trying to send a clear message about the values involved; alternatively, free-riding and strategic behavior may explain the inability to observe higher consumer valuations of green energy in the residential sector. Finally, this paper has demonstrated the usefulness of quantile regression in accommodating censoring and unobserved heterogeneity in a single framework. This approach helps unravel, inter alia, non-linear effects that otherwise are difficult to disentangle.

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Appendices

A Differences between the Tobit, Cragg's truncated normal hurdle model and the Exponential Type II Tobit (ET2T) models

We provide a very brief description of the differences between these three models, a more detailed description of which may be found in Wooldridge (Chapter 17 2010) and Jones (1992) among others. We introduce two variables, Y_i the observed wtp, W^* the unobserved latent variable which determines wtp, and s_i an indicator for $Y_i = 0$. Y_i is determined as

$$Y_i = s_i W^*.$$

Two-part models (hurdle models) make one of two assumptions; the more restrictive is

$$D(W^*|s,X) = D(W^*|X),$$

with $D(.|.)$ a conditional distribution, or the less restrictive

$$\mathbb{E}(W^*|s,X) = \mathbb{E}(W^*|X),$$

with $\mathbb{E}(.|.)$ a conditional expectation.

Using the latter, therefore, the equation of interest is

$$\mathbb{E}(Y_i|s_i,X_i) = s_i\mathbb{E}(W^*|s,X) = s_i\mathbb{E}(W^*|X) \tag{A.1}$$

For $s_i = 1$, eq. (A.1) is simply

$$\mathbb{E}(W^*|X) = \mathbb{E}(Y_i|Y_i > 0, X_i). \tag{A.2}$$

Using the law of iterated expectations and eq. (A.1),

$$\mathbb{E}(Y_i|X_i) = \mathbb{E}(s_i|X_i)\,\mathbb{E}(W_i^*|X_i) = \mathbb{P}(s_i = 1|X_i)\,\mathbb{E}(W_i^*|X_i) \tag{A.3}$$

Cragg's truncated normal hurdle model is essentially eq. (A.3), with two assumptions: $W^*$is distributed as truncated normal on $(0,\infty)$and $\mathbb{P}(s_i = 1|X_i) = \mathbb{P}(Y_i > 0|X_i) = \Phi(X_i\beta)$i.e. a probit model, and the two parts of the model in eq. (A.3) have independent parameters. Thus, the probit can be estimated independently of the truncated regression. This also explains why the number of observations used in the probit and the truncated regression parts are different for the TNH model, in the tables reported.

To understand the ET2T model , consider instead the following log normal hurdle model:

$$Y_i = s_i W_i^* = \mathbb{I}(X_i\gamma + \nu > 0)\exp(X_i\beta + u)\,, \tag{A.4}$$

with $\nu_i|X \sim N(0,1)$ (as is typical in probit models) and $u_i|X \sim N\left(0,\sigma^2\right)$. This last implies, in particular, that $W_i^* = \exp(X_i\beta + u)$ has a log normal distribution. When $\gamma = \beta$ and $\nu|X$ and $u|X$ are uncorrelated, the model in eq. (A.4) is a log normal hurdle model; if $\gamma \neq \beta$ and $\nu|X$ and $u|X$ are correlated, the ET2T model is obtained. The derivation of the likelihood function is a bit involved (see Wooldridge (2010, Chapter 17, 697-8)) but is similar to that of the Heckman selection model, labeled the Tobit Type II model. The main issue involved here, as in the Heckman-style models, is that for proper identification, the two sets of covariates in the participation and amount decisions must differ in at least one dimension. Again, similar to the tobit model, due to the joint estimation of both the participation and amount decisions, the number of observations used will be identical for the two tables in the main text (table 3 and table 4) for this particular method.

B Inference in the CQIV framework

An important point not so far directly addressed is that regarding inference in this framework. In more detail, typical inference in the QR setting addresses the following two questions: Are all (or selected) coefficients identical across quantiles (implying conditional mean models are equally valid)? Is the quantile process statistically significant, a question of goodness-of-fit (see for instance Koenker & Machado (1999), Koenker & Xiao (2002)). Given however the relatively complicated estimation framework used in the censored QR here, it is both challenging to compute the cross-quantile variance-covariance matrix (using weighted bootstrap, which is the inference option chosen) as well as, given the population weights, unclear which procedures are valid. As a result, we do not report any overall goodness-of-fit statistic here. In addition, given the computational complexity of the bootstrap, the "cqiv" procedure used (Chernozhukov et al. (2012)) does not permit computation of the whole variance-covariance matrix (across quantiles); as a result, the alternative approach to inference, the Wald test approach, is also unavailable. Finally, for similar reasons, it is a difficult task (and one not supported by the "cqiv" procedure we use here) to compute "predicted values" at each estimated quantile.

Essentially, the computational complexity of the procedure implies that, so far at least, only the coefficient(s)/marginal effects and their confidence intervals are the only easily computable or interpretable objects, and we restrict ourselves to it here.

C Additional Tables

Author	Country	Method	Dependent variable	Demographics	Economics	Attitudes	Others
Yoo & Kwak (2009)	Korea	Spike model	indicator for: wtp for green electricity		Bid (-), Income (+)		
Gerpott & Mahmudova (2010)	Germany	Partial least squares	5-scale agreement for wta green electricity			Social endorsement (+), Environmental protection attitude (+)	Switching difficulty (-)
Gerpott & Mahmudova (2010)	Germany	Logistic regression, Ordinal regression	Six-rank wtp a mark-up for green electricity	Household size(+), Age(-)	Electricity bill(-)	Attitude towards environment and current supplier (+), Social reference group(+)	Ecological conservation behavior(+)
Ozaki (2011)	UK	Correlation	5-point scale for adoption intention			Attitude towards green electricity (+), Social influence (+), Normative beliefs (+), Controllability (+), Information (+)	
Oliver et al. (2011)	South Africa	Logistic regression	Indicator for wtp a premium for green electricity		Income(+), Everyone should contribute(+)	Reliable attitude(+)	Recycle behavior(+)
Hansla (2011)	Sweden	OLS	Five-point scale for likelihood of paying a surcharge for eco-labeled electricity		Surcharge(-)	Biospheric framing(+), Self-transcendence value(+)	
Abdullah & Jeanty (2011)tnotea	Kenya	Double bounded model	wtp for PV electricity	House ownership(+), Age(-)	Income(+), Bid (-)	Interested in business(+)	
Zorić & Hrovatin (2012)tnoteb	Slovenia	Tobit and Double hurdle models	wtp for green electricity	Age(-)	Income(+), Electricity bill(+)	Environmental awareness(+)	
Strazzera et al. (2012)	Italy	Double bound model	wtp a bid for solar energy	Urban(+), In energy sector(+) , Home green tech(+)	Bill(+)	Health risk perception(+), Photovoltaic pollution perception(-), Invest heavy industry(+)	Coal information(+), Contact Energy Agency(+)
Liu et al. (2012)	China	Logit model	Indicator for wtp for renewable energy	Age(-)	Income(+)	Belief about the cost(+), Knowledge (+)	
Ertör-Akyazı et al. (2012)	Turkey	Logit model	Endorsement of renewable energy	Education(+)		Knowledge of climate change(+), Environmental optimism (-), Environmental concern(+), Economy-oriented(-)	
Zhai & Williams (2012)	US	Fuzzy logit model	Indicator for Adoption of photovoltaics			Environmental concern(+), Perceived cost of solar panels(-), Perceived maintenance requirement(-)	

[a] The result is for photovoltaic of monthly payment. [b] These factors influence the amount of WTP. The decision of participation is determined by age, education, and environmental awareness.

Table C.1: Summary of recent studies on WTP for “green” energy.