Indirect Estimation of Willingness to Pay for Energy Technology Adoption

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Abstract

Adopting energy-efficient and clean technologies is key to climate change mitigation and meeting long-term sustainability goals because they significantly reduce energy consumption and related carbon emissions. Understanding existing barriers and drivers for the adoption of these energy-efficient and clean technologies will be crucial to meeting ambitious national energy and emissions targets, and the customers' willingness to pay (WTP) is a key factor in understanding the potential for scaling-up adoption. However, in practice, commonly-used WTP estimation methods such as survey or purchase experiments are not always practical or feasible due to budget, time, labor or data constraints. This study proposes a new constrained optimization-based indirect estimation of WTP for energy technology adoption using customers' implicit life-cycle cost-benefit analysis and market data. The empirical probability distribution of WTP is estimated using the Monte Carlo methods. This new indirect estimation method provides a deeper understanding of the barriers and customers' willingness to adopt high efficiency and clean energy technologies, and informs the development of supporting policies and programs needed to accelerate market adoption.

Keywords: energy efficiency; technology adoption; discrete choices; willingness to pay; cost-benefit analysis; life-cycle analysis

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1. Introduction

Global primary energy consumption reached nearly 600 exajoules in 2018 and is projected to rise by 25 to 50 percent by 2050 under reference or business-as-usual scenarios of growth [1, 2]. Global carbon emissions from energy use are estimated to be more than 33 Gt of carbon dioxide (CO_2) in 2018 [2, 3]. Scaling up the adoption of energy-efficient and clean technologies[1] is critical to reduce energy consumption and CO_2 emissions and contribute to global efforts to meet long-term climate change mitigation and environmental sustainability goals [4].

Besides climate change mitigation, the adoption of energy-efficient and clean technologies can also potentially accrue both private and social positive returns in the form of economic, environmental, and other social benefits [5]. Furthermore, the world has seen an increasing number of pledges by governments and companies to reach net-zero carbon or greenhouse gas emissions in the coming decades, and the adoption of energy-efficient and clean technologies are inevitably a critical factor to achieve these ambitious net-zero emission targets [4, 6-9]. Techno-economic analysis of adopting energy-efficient and clean technologies has thus attracted growing attention due to its importance in both consumer and business decision-making theory and practices [10-14].

Despite the policies and programs adopted by governments and companies worldwide to increase the adoption of energy-efficient and clean technologies, there is a broadly held view that there are various barriers to the adoption of energy-efficient and clean technologies [5, 6, 15-17]. As pointed out by Gerarden et al. [5], on the one hand, energy efficiency technologies offer great potential in reducing energy-related costs, mitigating adverse environmental impacts, and increasing both private and social welfare; on the other hand, these promising technologies have not been widely adopted by customers and companies to the degree that would be expected based on estimated benefits from technology adoption modeling [5]. Potential explanations of this so-called "energy-efficiency gap" fall into three broad categories: market barriers, behavioral explanations, and modeling issues [5]. Some researchers [18] suggest that the actual magnitude of the energy-efficiency gap is relatively small compared to the assessments from some engineering analyses and there is also substantial heterogeneity in investment inefficiencies across the individuals and companies.

To accelerate the market uptake of energy-efficient and clean technologies, it is necessary to assess the barriers and drivers for the energy technology adoption [5, 6, 15, 16, 19-21]. By reviewing the barriers and drivers for energy technology adoption discussed in the literature, we think that, from the perspective of private individuals and companies, the following five factors are the major factors affecting energy technology adoption: availability, knowledge, affordability, net gain, and willingness. More specifically, (a) energy-efficient and clean technologies are not evenly available across spatial and temporal dimensions in the real-world; (b) the lack of knowledge and/or ability to recognize the technology adoption benefits together with individual or company's economic perspective may result in missed opportunities to adopt a technology that is theoretically justified for the individual or company; (c)

[1] We note that, throughout this paper, we use technology as a general terminology to refer to any energy technology or energy-related product, equipment, process, services or commodities [4], unless stated otherwise.

energy-efficient and clean technologies usually require higher initial investments and a lack of funding or availability of financing is a critical barrier to overcoming the capital costs of energy-efficient and clean technologies [6, 17, 19, 22, 23]; (d) the net gain (or net benefit) from adopting technology for a private individual or company is often a critical factor for consideration; and (e) the willingness of a private individual or company to adopt an affordable technology, which is highly related to all the above four factors, can be largely gauged by the willingness to pay (WTP) for adopting the technology.

In a standard economic view, WTP is defined as the maximum price at or below which a customer will definitely buy one unit of the product [24, 25]. In practice, WTP may be measured using different forms such as a ratio of two parameters; for example, it is a widely-used practice in applied economics to measure WTP for an attribute in a discrete choice model by using the ratio of a utility function attribute parameter to a cost parameter [26, 27]. Note that WTP is often viewed as a point measure [24] but sometimes conceptualized as a range [28, 29].

In general, accurately estimating customers' WTP is critical for the research and development of new technologies, implementing various pricing tactics and formulating competitive strategies [24], and supporting policymaking and program design. Several approaches have been developed for estimating WTP [24, 26, 30-33]. The major distinctions among the approaches are whether they estimate WTP directly or indirectly and whether they determine customers' hypothetical WTP or actual WTP [24]. In practice, some researchers may prefer the direct estimation method, such as asking customers directly to state their WTP for a specific technology, while others may favor an indirect approach such as choice-based conjoint analysis [24, 34-37]. It should be noted that both direct and indirect estimation methods can generate inaccurate results for various reasons, and more fundamentally, both methods estimate customers' hypothetical—rather than actual—WTP, and thus can induce hypothetical bias [24, 38].

Because customer WTP is individual- and context-sensitive [39, 40], the suitability of a particular WTP estimation method may depend on how well the method approximates the actual context for selecting and adopting the underlying technology [24]. Many studies suggest direct methods seem to be more suitable for relatively lower-priced non-durable product categories without direct and explicit competition, while indirect methods may be more suitable for relatively higher-priced durable product categories with significant competition [24, 36]. In the context of energy technology adoption, energy-efficient and clean technologies usually belong to the category of relatively higher-priced, infrequently purchased, and durable products, and thus in practice, customers' WTP for adopting energy-efficient and clean technology is often estimated using indirect methods; however, this does not mean that direct method is not suitable for estimating WTPs of energy technologies. Furthermore, in practice, the applicability of a particular WTP estimation method is also subject to many constraints, such as budget, time, and labor. A theoretically better method may not be practical or feasible due to various constraints, especially when commonly-used methods such as large-scale survey or purchase experiments are not feasible due to budget, time, labor, or data constraints.

This study proposes a new indirect estimation method of WTP for energy technology adoption using customers' implicit life-cycle cost-benefit analysis (iLCCBA) and market data. The empirical probability distribution of WTP is estimated using Monte Carlo methods and the policy implications of WTP for energy technology adoption are also discussed. This indirect estimation method provides a deeper understanding of market barriers affecting customers' willingness to adopt the energy-efficient and clean technologies, and supports and informs related policymaking and program design needed to overcome these barriers. The remainder of the paper is organized as follows. Section 2 describes this new methodology of indirect estimation of WTP and its empirical distribution using implicit life-cycle analysis and market data, and relative gain expectation for energy technology adoption. Section 3 presents results and discussions of two illustrative examples. Section 4 discusses potential limitations of this new methodology. Finally, Section 5 concludes with an overview of key findings and policy implications.

2. Methodology

2.1 Cost-benefit analysis as information for technology adoption

Cost-benefit analysis is necessary and important in technology selection [41, 42] and the selection of alternative technologies usually impacts both pending and future costs and benefits. Therefore, life-cycle cost analysis (LCCA) or more general life-cycle cost-benefit analysis (LCCBA) is often required and utilized to determine whether adopting specific technology is economically justified [43-46]. From the customer's perspective, the life-cycle cost is the total customer expense (e.g., purchase cost and operating cost) of specific technology over the life of the technology [5], while the life-cycle benefit is the total customer benefit associated with direct benefits (e.g., profit or efficiency) or other benefits from reducing negative impacts, losses or damages over the life of the technology. It should be noted that in LCCA or LCCBA, costs and benefits are usually expressed in monetary terms allowing the comparison of different types of costs and benefits in the same units. Estimating all costs and benefits in monetary terms also allows the calculation of net benefits, which is defined as the sum of all monetized benefits minus the sum of all monetized costs, and thus comparing different technology options in the same units [42].

Because costs and benefits usually occur in different time periods over the life of the technology, one commonly used method of rendering the cost and benefit estimates comparable is to discount the customer costs and benefits that occur in different time periods by expressing their values in present terms [42]. Specifically, the net present value (NPV) of a projected stream of current and future benefits and costs is estimated by multiplying the costs and benefits in each year by a time-dependent weight—known as a discount factor—and adding all of the weighted values as shown in the following equation [42]:

$$NPV = NB_0 + d_1 NB_1 + d_2 NB_2 + \cdots + d_n NB_n = \sum\nolimits_{t=0}^{n} d_t NB_t \ , \tag{1}$$

where: t is time period index, $t = 0,1,2,\cdots,n$; n is the final time period of the analysis period; $NB_t = Benefit_t - Cost_t$ is the net difference between benefit ($Benefit_t$) and cost ($Cost_t$) that accrue at the time period t; and d_t is the discounting weights, with $d_0 = 1$ and $d_t = 1/(1+r)^t$, where r is the real discount rate.

The choice of discount rate is very important and has a significant impact on cost-benefit analysis. We note that social discounting (i.e., discounting from the broad society-as-a-whole point of view) is usually used in cost-benefit analysis for policy analysis [42], while private discounting (i.e., discounting from the specific, limited perspective of private individuals or companies) may be appropriate for selection of technologies by private individuals or companies. For example, when a consumer chooses a durable product for a specific end-use, it is generally appropriate to use private discounting for the cost-benefit analysis. Research [5, 11, 47, 48] suggests relatively high average implicit discount rates for private customers when considering the adoption of energy-efficient technology, and thus private customers may significantly discount the future benefits from the new technology. Also, the discount rate may not be constant over the life of specific technology for a consumer. For example, a consumer may discount the near-future costs and benefits heavier than far-future costs and benefits, which suggests a larger implicit discount rate for discounting near-future costs and benefits and a relatively smaller implicit discount rate for discounting far-future costs and benefits.

NPV gives a comparable net benefit value for adopting a specific technology. Assume that there are N technologies for selection, the NPV of adopting each technology could be used to inform the selection. More specifically, let NPV_i, $i = 0, 1, \cdots, N-1$, denote the NPV of adopting technology T_i, it will maximize the total net benefit for adopting technology which has the maximum NPV, i.e., choosing the technology

$$T^* = \arg\max_i NPV_i = \sum_{t=0}^{n} d_t \cdot NB_{i,t} , \tag{2}$$

subject to some constraints such as budget or preferences.

We note that, although LCCA or LCCBA is usually required for policymaking and program design and evaluation, a private individual or company may not, or may not be able to, perform an LCCA or LCCBA for the technology adoption due to various reasons such as lack of information or time constraints. Sometimes, private individuals or companies may just perform a simple LCCA or LCCBA based on their specific preference or context. However, from the perspective of aggregate market activities, the market data such as sales over a certain time period reflect the private customers' collective preferences and choices based on their underlying estimates of the life-cycle net benefits from adopting the technology. We thus referred to this market aggregate implicit life-cycle cost-benefit analysis as customers' implicit LCCBA, or iLCCBA for short.

2.2 Indirect estimation of the WTP for technology adoption

Consider the following general framework of probability models for an individual choice among a set of alternatives [49]:

$$\mathrm{Prob}(Y = i \mid \mathbf{x}) = F(\text{relevant effects, parameters}, \mathbf{x}) \ \text{ for } \ i = 0, 1, \cdots, N-1 . \tag{3}$$

In a random utility view of the individual choice, for an individual faced with N choices, suppose that the utility of choice i is U_i for $i = 0, 1, \cdots, N-1$. If the individual makes a choice i in particular, then we assume that U_i is the maximum among the N utilities, and the statistical model is driven by the probability that choice i is made, which is Prob($U_i > U_k$) for all other $k \neq i$ [49].

We consider individual choices that are observed and revealed by data such as sales and purchase prices, mainly following Greene [49] and Train [14]. Specifically, we consider the following technology adoption model for specific end use:

$$s_{i,t} = \frac{v_{i,t}}{V_t} = \frac{a_{i,t} \cdot \exp(u_{i,t})}{\sum_{i=0}^{N-1} a_{i,t} \cdot \exp(u_{i,t})} , \tag{4}$$

where: $i=0,1,\cdots,N-1$ denotes the *i*th technology; $t=0,1,\cdots,M-1$ denotes the *t*th time period; $v_{i,t}$ is volume of sales of technology *i* for the specific end use in time period *t*; V_t is volume of total sales of all *N* technologies for the specific end use in time period *t*, i.e., $V_t=\sum_{i=0}^{N-1}v_{i,t}$; $s_{i,t}$ is share of sales of technology *i* for the specific end use in time period *t*; $a_{i,t}$ is availability of technology *i* for the specific end use in time period *t*; $u_{i,t}$ is utility of technology *i* for the specific end use in time period *t*.

We further consider a special form of the utility function:

$$u_{i,t}=U(w_{i,t},p_{i,t},\mathbf{c}_{i,t}) \text{ for } i=0,1,\cdots,N-1 \text{ and } t=0,1,\cdots,M-1, \tag{5}$$

where: $w_{i,t}$ is WTP for technology *i* for the specific end use in time period *t*; $p_{i,t}$ is the purchase price of technology *i* for the specific end use in time period *t*; and $\mathbf{c}_{i,t}$ is a vector of input parameters or control variables.

For simplicity, we assume that index $i = 0$ denotes the baseline technology, which usually has the least efficiency level among the set of technology choices, and $i=1,2,\cdots,N-1$ denotes each alternative technology that usually has higher efficiency level.

We note that the WTP for technology may change over time with the changes in costs, customer's awareness and knowledge of the technology, market transitions and policies. Therefore, it is valuable to investigate the dynamics of the WTP for a technology if relevant data are available.

The WTP for technology $i=0,1,\cdots,N-1$ in time period *t* can be estimated by the following nonlinear optimization problem:

$$\mathbf{w}_t^*=\arg\min_{\mathbf{w}_t} d(\hat{\mathbf{s}}_t,\mathbf{s}_t)=\|\hat{\mathbf{s}}_t-\mathbf{s}_t\| \tag{6}$$

where: $\mathbf{s}_t=(s_{0,t},s_{1,t},\cdots,s_{N-1,t})^T$ is a vector with component *i* representing the share of sales of technology *i* in time period *t*; $\hat{\mathbf{s}}_t=(\hat{s}_{0,t},\hat{s}_{1,t},\cdots,\hat{s}_{N-1,t})^T$ is a vector with component *i* representing the estimated share of sales of technology *i* in time period *t*, and $d(\hat{\mathbf{s}}_t,\mathbf{s}_t)=\|\hat{\mathbf{s}}_t-\mathbf{s}_t\|$ is a distance function. Note that, in practice, the above optimization problem is usually a constrained optimization problem.

The selection of distance function is usually dependent on the complexity and nonlinearity of utility function and measurement error. In most cases, the following non-linear least-squares optimization can be used for simplicity purposes:

$$\mathbf{w}_t^*=\arg\min_{\mathbf{w}_t} d(\hat{\mathbf{s}}_t,\mathbf{s}_t)$$

$$d(\hat{\mathbf{s}}_t,\mathbf{s}_t)=\sum_{i=0}^{N-1}\left(\hat{s}_{i,t}-s_{i,t}\right)^2=\sum_{i=0}^{N-1}\left(\frac{\hat{v}_{i,t}}{V_t}-\frac{v_{i,t}}{V_t}\right)^2. \tag{7}$$

We note that the basic idea behind the above method is to convert the estimation of WTP for technology adoption into a constrained optimization problem.

In practice, some parameters in the utility function may be unknown and need to be estimated. Suppose that, for example, we take the following special case of utility function by referring to the conceptual model described by Allcott and Greenstone [18]:

$$u_{i,t}=\phi_t(w_{i,t}-p_{i,t}) \text{ for } i=0,1,\cdots,N-1 \text{ and } t=0,1,\cdots,M-1, \tag{8}$$

where: purchase price $p_{i,t}$ is assumed to be known and coefficient ϕ_t and WTP $w_{i,t}$ need to be estimated. If we further assume that: a) the coefficient $\phi_t > 0$ is invariant during the time period t and only relevant to the individual expected surplus which is calculated as $(w_{i,t} - p_{i,t})$; and b) the individual expected surplus is the NPV from the individual iLCCBA described in the previous section, we thus could estimate coefficient ϕ_t by solving an optimization problem similar to Equation (7), specifically,

$$\phi_t^* = \arg\min_{\phi_t} d(\hat{\mathbf{s}}_t, \mathbf{s}_t)$$

$$d(\hat{\mathbf{s}}_t, \mathbf{s}_t) = \sum_{i=0}^{N-1} \left(\hat{s}_{i,t} - s_{i,t}\right)^2 = \sum_{i=0}^{N-1} \left(\frac{\hat{v}_{i,t}}{V_t} - \frac{v_{i,t}}{V_t}\right)^2 . \tag{9}$$

In practice, as coefficient $\phi_t > 0$ is assumed to be invariant during the time period t and only relevant to the individual's expected surplus, if we further assume that the WTP for each technology is zero and the purchase price of each technology is relative price to the baseline technology (i.e., the technology indexed as 0), the above parameter estimation could be further simplified.

It should be noted that the above estimation process implicitly assumes that $v_{i,t}$ (i.e., sales of technology i in time period t) for $i = 0, 1, \cdots, N-1$ can be observed or measured. In practices, the sales of some technologies may not be directly available. In this case, the sales of the technologies also need to be estimated for estimating the customer WTP for technology i. The survival analysis can be utilized to estimate the sales of the technologies given some necessary observations or measurements of other variables (e.g., technology stock or saturation rate) and survival function of the technology by making some assumptions.

2.3 Estimating empirical probability distribution of WTP based on Monte Carlo methods

The estimated customer WTP using the indirect method described in the previous section is a point estimate in nature. While a point estimate of customer WTP provides some information, it fails to adequately account for either the variability in customer WTP or the uncertainty in the input data, parameters and underlying economic assumptions. Generally speaking, a point estimate without accompanying statistics of the estimate or measure of precision is much less valuable.

As a best practice in informing decision-making, a risk and uncertainty analysis is one way to ascertain whether cost-benefit estimates are realistic, appropriate, and adequate as it can determine the probability associated with achieving the cost-benefit estimate [50]. Risk and uncertainty analysis provides a way to assess the variability in the estimate by quantifying costs, benefits, risks and uncertainties. A cost-benefit analysis can model such effects by changing input parameters based on their distributions and thus creating a range of potential cost-benefit estimate. A range of cost-benefit estimate is more useful to support the decision-making process than a point estimate as a range helps decision-maker better understand the varying outcomes of a cost-benefit analysis [50, 51].

In both theory and practice, the probability distribution of an estimate (e.g., customer WTP) is much preferable [50, 51]. One statistical technique for estimating the empirical probability distribution of an estimate is Monte Carlo method.

The Monte Carlo method is widely used to solve various stochastic problems in applied science and engineering. One major technique of the Monte Carlo method is Monte Carlo simulation [52]. Solving a stochastic problem by the Monte Carlo simulation usually involves three steps: 1) generating independent samples of the random parameters and functions in the definition of the stochastic problem; 2) solving the resulting deterministic problems corresponding to the samples generated in the prior step, and 3) analyzing statistically the collection of deterministic solutions to estimate properties of the solution of the stochastic problem [53].

Consider a sample of *m* observations $b_1, b_2, \cdots, b_m$, satisfying

$$b_i = g(x_i, \boldsymbol{\varphi} \mid \boldsymbol{\rho}) + \varepsilon_i , \tag{10}$$

where $i = 1, 2, \cdots, m$; x_i is independent variable; $\boldsymbol{\varphi} = [\varphi_1, \varphi_2, \cdots, \varphi_n]$ is a vector of parameters of interest that is to be estimated from the data; $\boldsymbol{\rho} = [\rho_1, \rho_2, \cdots, \rho_q]$ is a vector of input parameters (affecting factors) of which joint distribution is assumed to be known, and the estimate of $\boldsymbol{\varphi}$ is thus conditional upon $\boldsymbol{\rho}$; and ε_i is the error of the observations.

We note that, hereafter, $\boldsymbol{\varphi}$ is defined as the vector of WTP for a set of technologies and is estimated using aggregate market data and implicit life-cycle cost-benefit analysis. The uncertainty and errors in the market data, implicit life-cycle cost-benefit estimates and underlying economic assumptions will inevitably affect the estimation of the vector of WTP $\boldsymbol{\varphi}$. We can utilize the knowledge of the data and input parameters to conduct Monte Carlo simulation for estimating the vector of WTP $\boldsymbol{\varphi}$ and analyzing the properties of the estimate. More specifically, denote $\hat{\boldsymbol{\varphi}}$ as the estimate of vector of WTP $\boldsymbol{\varphi}$, we are interested in the properties and empirical distribution of the estimate $\hat{\boldsymbol{\varphi}}$ given the distribution of the vector of input parameters $\boldsymbol{\rho}$.

Based on the knowledge of the vector of input parameters $\boldsymbol{\rho}$, *L* sets of samples are randomly generated from a multivariate distribution:

$$\tilde{\boldsymbol{\rho}}_l \sim F(\boldsymbol{\rho}) \text{ for } l = 1, 2, \cdots, L , \tag{11}$$

where each element of the vector of input parameters $\boldsymbol{\rho}$ is a random variable. Note that these random variables—elements of the vector of input parameters $\boldsymbol{\rho}$—do not necessarily follow the same distribution and they also might or might not be correlated.

For each sample of the vector of input parameters $\tilde{\boldsymbol{\rho}}_l = [\tilde{\rho}_{l,1}, \tilde{\rho}_{l,2}, \cdots, \tilde{\rho}_{l,q}]$, where $l = 1, 2, \cdots, L$, we can then obtain an estimate $\hat{\boldsymbol{\varphi}}_l = [\hat{\varphi}_{l,1}, \hat{\varphi}_{l,2}, \cdots, \hat{\varphi}_{l,n}]$ for the vector of WTP $\boldsymbol{\varphi} = [\varphi_1, \varphi_2, \cdots, \varphi_n]$.

Consider the *i*th element φ_i of the vector of WTP $\boldsymbol{\varphi} = [\varphi_1, \varphi_2, \cdots, \varphi_n]$, the simulation sample mean $\bar{\hat{\varphi}}_i$, variance $Var_{\hat{\varphi}_i}$, standard deviation $\sigma_{\hat{\varphi}_i}$, skewness g_{1i}, and (excess) kurtosis g_{2i} can then be computed as follows [54, 55]:

$$\bar{\hat{\varphi}}_i = \frac{1}{L} \sum_{l=1}^{L} \hat{\varphi}_{l,i} , \tag{12}$$

$$Var_{\hat{\varphi}_i} = \frac{1}{L} \sum_{l=1}^{L} (\hat{\varphi}_{l,i} - \bar{\hat{\varphi}}_i)^2 , \tag{13}$$

$$\sigma_{\hat{\varphi}_i} = \sqrt{Var_{\hat{\varphi}_i}} , \tag{14}$$

$$g_{1i} = \frac{\sum_{l=1}^{L}\left(\hat{\varphi}_{l,i} - \bar{\hat{\varphi}}_i\right)^3 \Big/ L}{\left(\sigma_{\hat{\varphi}_i}\right)^3}, \text{ and} \tag{15}$$

$$g_{2i} = \frac{\sum_{l=1}^{L}\left(\hat{\varphi}_{l,i} - \bar{\hat{\varphi}}_i\right)^4 \Big/ L}{\left(\sigma_{\hat{\varphi}_i}\right)^4} - 3. \tag{16}$$

The empirical probability distribution of WTP for specific technology, say φ_i, can be further examined based on the L estimates $\hat{\varphi}_{i,1}, \hat{\varphi}_{i,2}, \cdots, \hat{\varphi}_{i,L}$. For convenience, we use the term "Monte Carlo estimation" to refer to the above method.

We note that the basic idea of the above Monte Carlo estimation is to build empirical models of feasible WTP estimations by Monte Carlo simulation combined with the indirect WTP estimation method using constrained optimization described in Section 2.2. More specifically, Monte Carlo simulation generates a large number of samples of the vector of input parameters based on the joint probability distribution for the input parameters (affecting factors, e.g., real discount rate) that have inherent uncertainties, and then constrained optimization is used to find the possible feasible solution to the WTP estimation problem based on each sample of the vector of input parameters. Put differently, for each sample of the vector of input parameters generated by the Monte Carlo simulation, constrained optimization is used to determine the feasibility of the optimization-based WTP estimation problem and to estimate the WTP if it is feasible. The empirical probability distribution of the WTP could then be constructed using those estimation results.

2.4 Relative gain expectation for technology adoption

Note that the above WTP estimate suggests customer willingness to pay for adopting some specific technology and usually reflects the private (individual or company) preferences and economic perspective, and it also supports analyzing the relative gain expectation for efficient and clean technology adoption.

For simplicity, we consider a simple two-technology case: one baseline technology (indexed as 0) and one more efficient technology (indexed as 1) during a certain time period.

We take the special case of utility function described by Equation (8) but drop the time index for simplicity purpose:

$$u_i = \phi \cdot \bar{g}_i = \phi(w_i - p_i) \text{ for } i = 0,1, \tag{17}$$

where: p_0 and p_1 are respectively the purchase price of the baseline technology and efficient technology; w_0 and w_1 are respectively the WTP for the baseline technology and efficient technology; $\bar{g}_i = w_i - p_i$, $i = 0,1$, is a gain (surplus) expectation; and ϕ is the gain coefficient. We note that the purchase price of a more efficient technology is usually, but not always, higher than the baseline technology.

Let $\tilde{p}_{0,1} = p_1 - p_0$ denote incremental price and $\tilde{w}_{0,1} = w_1 - w_0$ denote incremental WTP, define relative gain expectation $\tilde{g}_{0,1}$ as:

$$\tilde{g}_{0,1} = \bar{g}_1 - \bar{g}_0 = (w_1 - p_1) - (w_0 - p_0) = (w_1 - w_0) - (p_1 - p_0) = \tilde{w}_{0,1} - \tilde{p}_{0,1} \tag{18}$$

Note that $\tilde{g}_{0,1}$ reflects the relative expected gain change for a more efficient technology but with a higher price compared to the baseline technology.

We consider the following three possible cases:

$$\begin{aligned} &\text{Case I} \;\;: \tilde{g}_{0,1} = \tilde{w}_{0,1} - \tilde{p}_{0,1} < 0, \\ &\text{Case II} \;: \tilde{g}_{0,1} = \tilde{w}_{0,1} - \tilde{p}_{0,1} = 0, \\ &\text{Case III} : \tilde{g}_{0,1} = \tilde{w}_{0,1} - \tilde{p}_{0,1} > 0. \end{aligned} \tag{19}$$

The three cases in Equation (19) indicate that the incremental WTP can be respectively smaller than, equal to, or larger than the incremental price for adopting a more efficient technology rather than the baseline technology. In each of these cases, the sign of the relative gain expectation $\tilde{g}_{0,1}$ will depend on two factors that are embedded in Equation (19). The first factor is the price change for the more efficient technology compared to the baseline technology, and the second is the WTP change for the more efficient technology compared to the baseline technology. When the relative gain expectation $\tilde{g}_{0,1}$ is less than zero (i.e., Case I), it is less attractive, in terms of customer willingness, to adopt the more efficient technology rather than adopt the baseline technology. This will happen when the incremental WTP is lower than the incremental price ($\tilde{w}_{0,1} < \tilde{p}_{0,1}$) for adopting the more efficient technology. When the relative gain expectation $\tilde{g}_{0,1}$ is zero (i.e., Case II), it is indifferent, in terms of customer willingness, to adopt either the more efficient technology or the baseline technology. This will happen when the incremental WTP is equal to the incremental price ($\tilde{w}_{0,1} = \tilde{p}_{0,1}$) for adopting the more efficient technology. Finally, when the relative gain expectation is greater than zero (i.e., Case III), it is more attractive, in terms of customer willingness, to adopt the more efficient technology rather than the baseline technology. This will happen when the incremental WTP is greater than the incremental price ($\tilde{w}_{0,1} > \tilde{p}_{0,1}$) for adopting the more efficient technology.

We note that: a) the above simple case could be easily extended to more complicated multi-technology cases; and b) the above analysis could also be performed using derivatives and sensitivity analysis.

3. Illustrative examples

In this section, we present the results and analysis of two illustrative examples to demonstrate the potential application of the proposed indirect estimation method. Synthetic[2] but realistic market and economic data for two different examples of energy-use technologies are utilized to demonstrate findings and insights from this new method of estimating customer WTP for adopting more efficient technology. Specifically, the two examples are constructed based on a mix of public and synthetic data, as well as ongoing research. While the data used in these two examples are illustrative and do not represent any specific energy technologies, they represent realistic economic and market data for energy technologies. These two examples were selected because the estimated average WTP for the more efficient technology is higher than the average retail price in the first example, and lower than the average retail price in the

[2] Synthetic data are used to decouple the examples from specific energy technologies.

second example. The iLCCBA and Monte Carlo methods are used to evaluate the potential underlying factors impacting customer WTP in each example and findings and insights from using this method.

We take the special case of utility function described by Equation (8) for both examples to show the basic idea of the methodology. The coefficient of expected gain ϕ_t is estimated by utilizing iLCCBA and mathematical optimization that is subject to the constraint $\phi_t > 0$. We further assume that the customer WTP for the baseline technology is equal to the average retail price of the baseline technology for simplicity purpose. We note that, in a two-technology case, the estimation of ϕ_t and WTP for the more efficient technology could be actually solved directly from the Equation (4) based on the above assumptions, while a numerical optimization is usually required for a general case or choice among more than two technologies.

3.1 Illustrative example 1

The first illustrative example considers one baseline technology BT_1 and one efficient technology ET_1 for a specific energy end-use application. The data used for the estimation are listed in Table 1 and input parameters and assumptions are listed in Table 2. As shown in Table 1, the volume of sales of the efficient technology ET_1 is larger than baseline technology BT_1 even though the average retail price of ET_1 is higher than BT_1. This suggests that the relative gain expectation for ET_1 is larger than zero. As shown in Table 2, ET_1 has lower average installation and operation and maintenance (O&M) costs, which could lead to a larger net benefit of adopting ET_1 compared to BT_1 despite a higher retail price for ET_1.

From the customer perspective, it is reasonable to assume based on the data that the average life-cycle net benefit of adopting ET_1 is greater than that of adopting BT_1. We therefore assume that the market-aggregate average NPV of adopting ET_1 is larger than BT_1.

Table 1. Data used for baseline technology BT_1 and efficient technology ET_1.

Data	BT_1	ET_1
Volume of sales (unit)	14305	20122
Average retail price ($/unit)	5660	6390

Table 2. Parameters and assumptions for baseline technology BT_1 and efficient technology ET_1.

Parameters and assumptions	BT_1	ET_1	Correlation coefficient
Installation cost ($)	$TN(\mu,\sigma^2,a,b)$, μ=1920, σ=192, a=0, b=3840	$TN(\mu,\sigma^2,a,b)$, μ=1130, σ=113, a=0, b=2260	0.7
Annual O&M cost ($)	$TN(\mu,\sigma^2,a,b)$, μ= 597, σ=60, a=0, b=1193	$TN(\mu,\sigma^2,a,b)$, μ= 489, σ=49, a=0, b=978	0.8
Lifetime expectation (year)	12		
Real discount rate	$\upsilon(a,b)$, a=3%, b=100%		

Note: O&M stands for operation and maintenance. $TN(\mu,\sigma^2,a,b)$ denotes truncated normal distribution of parent normal distribution $N(\mu,\sigma^2)$ with mean μ, standard deviation σ, lower truncation point a and upper truncation point b ($a < b$). $\upsilon(a,b)$ denotes uniform distribution with minimum a and maximum b ($a < b$).

The estimation results are shown in Figure 1 and Table 3. As shown in Figure 1 and Table 3, the estimated mean WTP ($6768) and median WTP ($6703) for efficient technology ET_1 are higher than the average retail price ($6390). This indicates that the market-aggregate expected gain from adopting ET_1 is higher than BT_1 and thus more individuals choose ET_1 over BT_1, which results in a larger market share for ET_1. It is worth noting that the estimated empirical distribution of WTP for ET_1 is right skewed due to the constraint $\phi_t > 0$ and that the market-aggregate expected NPV from adopting ET_1 is higher than BT_1.

Table 3. Estimated willingness to pay for adopting efficient technology ET_1.

Summary statistics	Willingness to pay for ET_1
Mean ($)	6768
Median ($)	6703
Standard deviation ($)	274
Skewness	1.55
Kurtosis	3.19

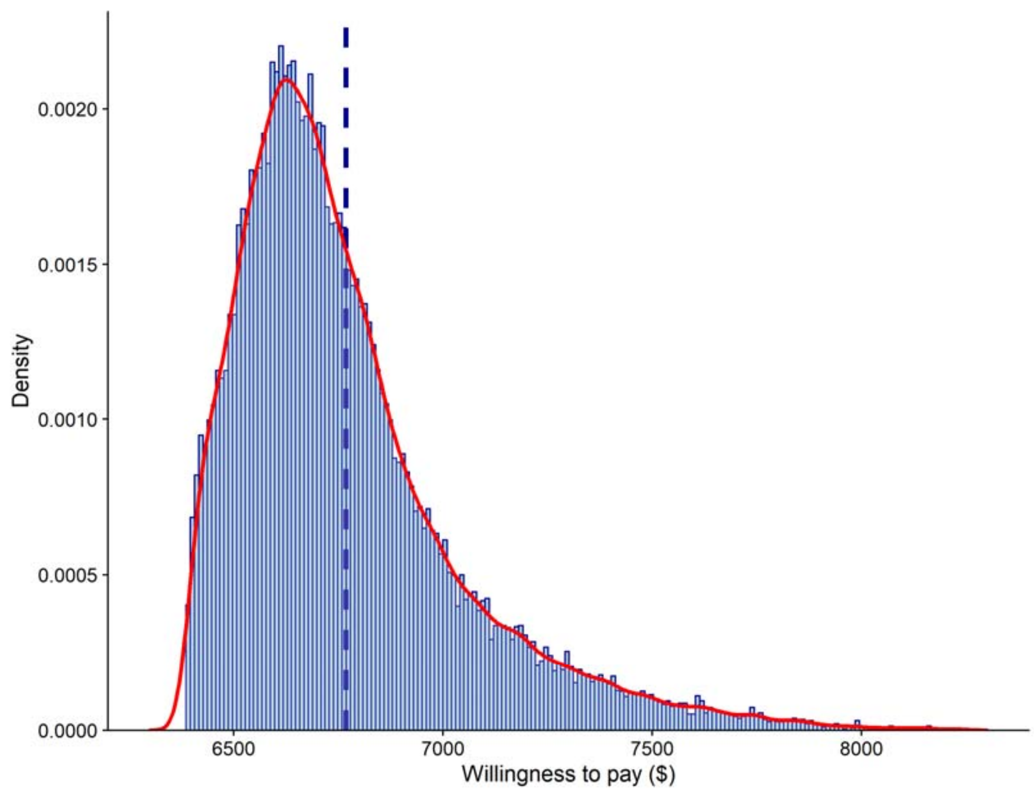

Figure 1. Willingness to pay (WTP) for adopting efficient technology ET_1.

Note: the blue dashed line denotes estimated mean WTP, and red line denotes estimated kernel density.

3.2 Illustrative example 2

The second illustrative example considers a different example where the average retail price of the more efficient technology ET_2 is higher than the baseline technology BT_2, and the volume of sales of ET_2 is less than BT_2. The data used for this estimation are listed in Table 4 and the input parameters and assumptions are listed in Table 5. As shown in Table 4, the average retail price of ET_2 is higher than the baseline technology BT_2, and the volume of sales of ET_2 is less than the baseline technology BT_2. This suggests the relative gain expectation for adopting ET_2 is less than zero. As shown in Table 5, ET_2 has a higher average installation cost and a lower average O&M cost. In this case, the customer could only recover the increased total purchase cost—assumed to be the sum of purchase price and installation cost in this case—of ET_2 through a decreased O&M cost, which would depend on the future usage of the technology and associated economic factors such as energy prices. We note that, for simplicity, we only consider economic costs and benefits that could be directly quantified in monetary terms and exclude additional non-monetary benefits such as greater convenience, operational control or comfort that an energy-efficient and clean technology may provide.

Because the volume of sales of ET_2 is less than BT_2, it is reasonable to assume that, from the customer perspective, the average life-cycle net benefit of adopting ET_2 is smaller than BT_2. Specifically, we assume that the NPV of adopting the more efficient technology ET_2 is smaller than the baseline technology BT_2.

Table 4. Data used for the baseline technology BT_2 and efficient technology ET_2.

Data	BT_2	ET_2
Volume of sales (unit)	4942	2946
Average retail price ($/unit)	9060	11075

Table 5. Parameters and assumptions for baseline technology BT_2 and efficient technology ET_2.

Parameters and assumptions	BT_2	ET_2	Correlation coefficient
Installation cost ($)	$TN(\mu, \sigma^2, a, b)$, $\mu = 3700$, $\sigma = 370$, $a = 0$, $b = 7400$	$TN(\mu, \sigma^2, a, b)$, $\mu = 4400$, $\sigma = 440$, $a = 0$, $b = 8800$	0.8
Annual O&M cost ($)	$TN(\mu, \sigma^2, a, b)$, $\mu = 2803$, $\sigma = 280$, $a = 0$, $b = 5606$	$TN(\mu, \sigma^2, a, b)$, $\mu = 2560$, $\sigma = 256$, $a = 0$, $b = 5120$	0.9
Lifetime expectation (year)	15		
Real discount rate	$BP(a, b, c)$, $a = 3\%$, $b = 30\%$, $c = 40\%$		

Note: O&M stands for operation and maintenance. $TN(\mu, \sigma^2, a, b)$ denotes truncated normal distribution of parent normal distribution $N(\mu, \sigma^2)$ with mean μ, standard deviation σ, lower truncation point a and upper truncation point b ($a < b$). $BP(a, b, c)$ denotes a beta-PERT distribution with minimum a, likeliest b, and maximum c ($a < b < c$).

As shown in Figure 2 and Table 6, the estimated empirical distribution of WTP for ET_2 is generally symmetric and bell-shaped with a mean value of $9259 and a standard deviation of $550. The estimated mean WTP ($9259) and median WTP ($9227) for the efficient technology ET_2 are notably lower than the average retail price ($11075). This indicates that the market-aggregate expected gain from adopting ET_2 is lower than baseline technology BT_2 and thus less individuals choose efficient technology ET_2 over baseline technology BT_2, which results in a larger market share for baseline technology BT_2. Note that the estimation is subject to constraint $\phi_t > 0$.

Table 6. Estimated willingness to pay for adopting efficiency technology ET_2.

Summary statistics	Willingness to pay for ET_2
Mean ($)	9259
Median ($)	9227
Standard deviation ($)	550
Skewness	0.31

Kurtosis	0.18

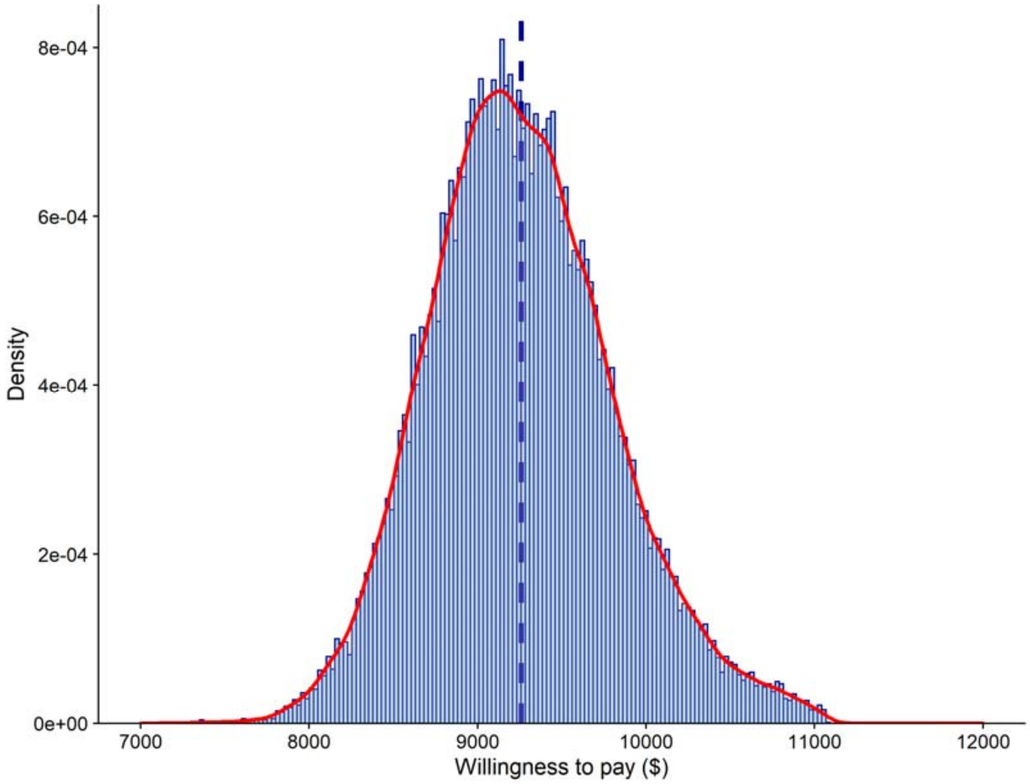

Figure 2. Willingness to pay (WTP) for adopting the more efficient technology ET_2.
Note: the blue dashed line denotes estimated mean WTP, and red line denotes estimated kernel density.

4. Limitations and discussions

While the above optimization-based indirect WTP estimation method using implicit life-cycle analysis and market data can be useful in several ways, it is essential to recognize the limitations of the method. We note the following potential limitations:

First, the estimate is the implicit customer WTP for the technology at an aggregate level. More precisely, this method develops an estimate of the relative market aggregate WTP for a technology over a time period, not an individual customer's WTP. As a market aggregate WTP, this estimate can provide some insights on the aggregate customer preferences and willingness to pay towards a technology.

Second, the market data used in this method may be incomplete, non-representative, uncertain and noisy, which could lead to inaccurate and biased estimates. High quality market data are generally required to draw reliable information based on the data. In practice, uncertainties and possible errors in the data should be carefully considered and evaluated. Furthermore, market data are usually historical data and may not be readily available for new technologies which have not been widely introduced to the market [56].

Third, life-cycle analysis requires a comprehensive understanding of the costs and benefits as well as techno-economic assessment. For example, how customers discount future costs and benefits and value losses and gains are usually context-specific and can vary significantly across individuals and companies, and change over time.

Last, the WTP estimated using the optimization-based indirect method is dependent on the underlying economic assumptions and customers' utility function. Specific customer preference on technology adoption often plays an important role in the technology adoption choices but some may be more difficult to quantify or express solely using monetary terms, and therefore requires tentative modeling of the utility underlying customer choice. For example, building energy efficiency technologies can provide multiple benefits for the building occupants including improved convenience, operational control or increased thermal comfort, moderated indoor temperatures, low humidity, and better indoor air quality [6]. However, these benefits are usually individual- and context-sensitive, making it difficult to accurately quantify the economic value of these benefits. Instead, these benefits are often broadly represented using general but reasonable assumptions in modeling.

Nevertheless, we note that this method provides some insights on indirectly estimating the WTP based on customers' implicit life-cycle analysis and market data, and thus on understanding customer preferences and willingness to adopt a specific technology. The method is particularly applicable in cases where commonly-used methods such as survey or purchase experiments are not feasible due to budget, time, labor or data constraints. The indirect estimation method presented in this paper could therefore be a good starting point for discussion and further research given the importance of customers' WTP on efficient and clean energy technology adoption.

5. Conclusions

To accelerate the adoption of energy-efficient and clean technologies, it is necessary and important to assess the barriers and drivers for energy-efficient and clean technology adoption. We think that—from the perspective of private individuals and companies—availability, knowledge, affordability, gain, and willingness are among the major factors affecting energy technology adoption.

Willingness to pay (WTP) can largely be used to gauge the willingness of a private individual or company to adopt a specific energy technology and thus has important implications for increasing the market adoption of energy-efficient and clean technologies. Estimation of the WTPs for energy technologies from the perspective of private individuals or companies is important for informing the development of supporting policies and programs for deploying and scaling up energy-efficient and clean technologies. However, there are many existing challenges to understanding customer behavior, implicit cost-benefit analysis, decision-making, and how these factors affect the customers' WTP, especially when some commonly-used WTP estimation methods are not practical or feasible due to budget, time, labor or data constraints.

This study proposes a new indirect method for estimating the WTP for energy technology adoption using customers' implicit life-cycle cost-benefit analysis and market data. This new approach essentially converts the estimation of WTP for energy technology adoption into a constrained optimization problem. The empirical probability distribution of WTP for energy technology adoption is further estimated using the Monte Carlo methods and the policy implications of WTP for energy technology adoption are also addressed. Two illustrative examples of this method using synthetic but realistic economic and market data are used to demonstrate the feasibility and advantages of this method.

Relative gain expectation—which can be estimated using incremental WTP and incremental price—reflects the relative expected gain change for a more efficient technology but with a higher price compared to the baseline technology. From the perspective of policymakers, different cases of the relative gain expectation have different implications. When the relative gain expectation is less than zero, the incremental WTP is outpaced by the incremental price for the more efficient technology and the customer is less willing to adopt the more efficient technology, which indicates that there may be barriers or disincentives to customer adoption. In this case, the possible barriers (e.g., lack of awareness or knowledge, or financial difficulty) or disincentives need to be identified and evaluated to inform the development of education, awareness, or incentives programs to make the efficient technology more competitive by reducing the incremental cost or increasing the customer WTP for the efficient technology. When the relative gain expectation is zero, there is no difference for the customer (assuming that the customer's preference will be determined only by gain expectation), in terms of willingness to adopt either the efficient technology or the baseline technology. This suggests that it is reasonable to expect, even without further policy interventions such as incentives, the more efficient technology is at least as market competitive as the baseline technology. Because the baseline technology will likely be gradually replaced by the more efficient technology given the potential additional benefits of the more efficient technology, policy intervention may not be necessary in this case. When the relative gain expectation is greater than zero, the incremental WTP outpaces the incremental price for the more efficient technology, and the customer is more willing to adopt the more efficient technology rather than the baseline technology. It suggests that the more efficient technology can be considered a market success to a large extent, in terms of both efficiency improvement and competitiveness enhancement. Generally speaking, policy intervention may not be needed in this case unless aiming for significantly accelerating the adoption of the more efficient technology.

Finally, the indirect WTP estimation method has several potential limitations. First, the estimate is the implicit customer WTP at an aggregate level, rather than for a specific customer, for a technology. Second, incomplete, non-representative, uncertain or noisy market data could lead to inaccurate and biased estimates. Third, life-cycle analysis requires a comprehensive understanding of the costs and benefits as well as techno-economic assessment. Fourth, the WTP estimated is dependent on the underlying economic assumptions and customers' utility function. Despite these potential limiting factors, this indirect estimation method sheds more light on deeper understandings of existing market barriers and customers' willingness to adopt energy-efficient and clean technologies, and supports policymaking and program design to address existing barriers.

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