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Abstract

The impacts of climate change are already visible throughout the world. Recognizing the threats posed by climate change, the Durban Platform, the 17th Session of the Conference of Parties (COP 17), underscores that the global nature of climate change calls for the widest possible cooperation and ambitious action by all countries. A crucial starting point for the design of effective and publicly acceptable policies is to explore public preferences for climate policy instruments. Using a choice experiment, this study investigates public preferences for carbon tax attributes in a developing country context. The results account for heterogeneity in preferences and show that Turkish people prefer a carbon tax with a progressive cost distribution rather than one with a regressive cost distribution. The private cost has a negative effect on the probability of choosing the tax. Earmarking carbon tax revenues increases the public acceptability of the tax. Moreover, there is a preference for a carbon tax that promotes public awareness of climate change.

Keywords: Carbon taxes, Choice experiment, Latent class model, Mixed logit model, Preferences, Turkey

JEL classification: H,Q

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1 Introduction

Anthropogenic climate change is one of the major issues facing the planet. There have been many international efforts to draw attention to the importance of the problem. The United Nations Framework Convention on Climate Change (UNFCCC) at the Rio de Janeiro Conference in 1992 was the first step taken at an international level to tackle the threat of climate change. The important point UNFCCC emphasizes is that all countries have common but differentiated responsibilities in mitigating climate change (Breindenich et al., 1998). The other remarkable initiative taken at the global level was the Kyoto Protocol in 1997, which set a target only for developed countries. However, the 17^{th} Conference of Parties (COP) organized in Durban in 2011 pointed out that not only developed countries but also developing countries will have some responsibilities, starting from 2020, to achieve global participation in mitigation efforts.[1]

Turkey became a party to the UNFCCC in 2004 and ratified the Kyoto Protocol in 2009.[2] However, it did not have any mitigation commitments between 2008 and 2012. During this period, the only obligation of Turkey was to monitor greenhouse gas (GHG) emissions from all sources. In 2011, the Ministry of the Environment and Urbanization released Turkey's first National Action Plan on Climate Change, which outlines the main problems associated with climate change and underscores the priorities to mitigate them, but the Action Plan does not set a target to reduce GHG emissions. In practice, Turkey has little experience of implementing market-based climate policy instruments. To date, it has engaged in the voluntary carbon market, which is not regulated under any official legislation.[3] In terms

[1] Taking into consideration all greenhouse gas (GHG) emissions in countries during the 1850-2010 period, den Elzen et al. (2013) provide evidence that the contribution of developing countries to global cumulative emissions will surpass that of developed countries within a decade.

[2] Turkey, as an OECD country, was included in Annex I and Annex II of the UNFCCC, together with the developed countries, in 1992. After lengthy debates at various UNFCCC meetings, Turkey's special case was recognized and its name was removed from Annex II with decision 26/CP.7 of the Seventh Conference of Parties (COP) in Marrakesh in 2001. Turkey acceded to the UNFCCC as the 189^{th} party on 24 May 2004.

[3] Liese et al. (2012) provide a good overview of the state of the Turkish voluntary carbon market. As of June 2012, Turkey had hosted 146 listed and registered projects in the field of wind, geothermal, hydropower, and municipal waste, of which 103 were under the Gold Standard and the rest were under the Verified Carbon Standard.

of using taxation as a pricing strategy to reduce GHG emissions from transportation, the Turkish Finance Ministry has recently announced a plan for restructuring vehicle taxes. Under the new scheme, the taxes will be based on the amount of pollution generated by a vehicle rather than its engine size and age. As a rapidly growing country with a high demand for energy products, Turkey has to design an effective climate change policy in the near future to comply with its commitments under the UNFCCC.[4] Given the fact that climate change mitigation is one of the priorities of the European Union (EU) environmental policy, the implementation of a more ambitious and coordinated climate change policy would also serve to demonstrate Turkey's readiness to fulfill its EU membership obligations. Using a choice experiment approach, this study explores public preferences for carbon tax (CT) attributes in Turkey. We believe that investigating public preferences is a useful starting point to the design of effective and publicly acceptable mitigation policies. Moreover, the policy implications of our findings may be particularly relevant to the implementation of market-based climate policy instruments in developing countries.

The acceptability and efficiency of climate policy instruments have been extensively discussed in the literature.[5] Researchers mostly employ a contingent valuation method to calculate the public's willingness to pay (WTP) for reductions in GHG emissions.[6] The number

[4]Turkey's rapid development between 1990 and 2011 resulted in a 119% increase in GHG emissions (UNFCCC, 2013)

[5]Stavins (1997) discusses frameworks and instruments that individual nations and groups of nations can adopt to achieve their climate goals. He also points to domestic and international institutional impediments to their implementation in practice. Baranzini et al. (2000) evaluate CTs with respect to their competitiveness, distributional, and environmental impacts. Sumner et al. (2009) review CT policies around the world and evaluate the effectiveness of existing CTs. Lorenzoni et al. (2007) explore the barriers that citizens and communities face in mitigating climate change. They also discuss possible policy measures that increase public participation in mitigation efforts in the United Kingdom.

[6]Carlsson et al. (2012) provide a good review of studies that employ a contingent valuation method to calculate the public's WTP to reduce GHG emissions. Using a contingent valuation method, Adaman et al. (2011) measure Turkish urban households' WTP for CO_2 emission reductions and investigate the determinants of their WTP. They provide evidence that the majority of people in Turkey are very willing to contribute to climate change mitigation projects. Consistent with the existing literature, they find that not only individuals' socio-economic characteristics but also their attitudes and awareness towards environmental issues have a significant effect on the self-reported WTP figures. Moreover, Ertör-Akyazı et al. (2012) conduct a survey to explore Turkish citizens' preferences for renewable and nuclear energy. They show that the majority of respondents endorse renewable energy sources such as wind and solar even if investments in these energy sources result in a 25 percent increase in their electricity bills, indicating Turkish citizens' willingness to contribute to climate change mitigation policies.

of studies using the choice experiment (CE) method to investigate public preferences for climate policy instruments is limited. Using an internet-based CE, Brannlund and Persson (2012) investigate peoples' preferences for climate policy instruments in Sweden. They show that Swedes do not like the use of tax as a policy instrument and prefer instruments with a positive effect on environmentally friendly technology and climate awareness. In addition, instruments with a progressive cost distribution are preferred to those with a regressive cost distribution. Saelen and Kallbekken (2011) conduct a CE to examine to what extent earmarking revenues from a fuel tax increases the public acceptability of this instrument in Norway. They provide evidence that earmarking increases acceptability because people do not believe that the tax is environmentally effective without earmarking. Bristow et al. (2010) use a CE to explore the impact of design attributes on the public acceptability of personal carbon trading and carbon tax in the United Kingdom. They find that design has a significant impact on the public acceptability of both measures. Our study contributes to the literature on this scant number of CE studies by analyzing public preferences for CT attributes in a developing country context.

In our CE, we propose CTs as a climate policy instrument for the following reasons.[7] First, by setting a clear price on emissions, CTs encourage polluters to adopt greener practices and promote renewable energy policies. For instance, a higher price on carbon emissions may lead to increased investment in cleaner energy sources such as solar and wind power.

[7]Climate change leads to a negative externality that has to be internalized through government policies. The International Panel on Climate Change (IPCC) suggests the following climate policy instruments to tackle this issue: CTs, tradable permits, subsidies, voluntary agreements, and information instruments. Economists strongly favor market-based instruments such as CTs and emission trading as they are cost efficient. The application and effectiveness of market-based instruments has been the subject of much research (EEA, 1996; EEA, 2000; Herber and Raga, 1995; OECD, 1997; OECD, 2001; OECD, 2006). From the economic point of view, the objective of CTs is to ensure that all the external costs associated with climate change are fully taken into account (Pigou, 1920). In practice, this raises some difficulties concerning the estimation of the accurate external cost of climate change (McKay et al., 1990; Smith 1992). Therefore, the primary purpose of CTs is to provide incentives for polluters to emit less carbon rather than fully internalize the external cost associated with climate change. In addition, Weitzman (1974) shows that in theory, CTs and emission trading are equivalent in terms of efficiency and effectiveness. However, in the case of uncertainties about the cost and damage functions, a CT fixes the price of carbon but does not give certainty about emissions reduction whereas emission trading allows uncertainty on the price of carbon but provides certainty about emissions reduction (Montero, 2002).

Second, in addition to being transparent and simple, a CT can be applied across all major emissions sources of the economy. Third, CTs are easier for governments to implement compared to other market-based instruments as policy makers can rely on the well-established administrative structure of existing taxes. For example, a cap-and-trade system requires a totally new administrative structure that facilitates the establishment of an efficient emissions trading market. In spite of these advantages, the adoption of a CT has been limited due to concerns about its impact on income distribution and international competitiveness.[8] A CT may curtail international competitiveness by adversely affecting the energy-intensive firms and industries that compete in an international market. However, Porter (1991) and Porter and van der Linde (1995) point out that environmental regulations often cause firms to be more efficient and competitive in the long run by triggering technological innovation and production efficiency. Even if there is a close link between the adoption of a CT and the loss of international competitiveness, the potential negative consequences might be significantly mitigated through a properly designed set of measures such as the use of the tax revenue to lower corporate income taxes. Another way of mitigating the competitiveness problem is to implement border tax adjustments (BTAs) on imports from countries with no carbon restrictions. BTAs essentially aim to remove any comparative advantage that foreign producers have because of less stringent environmental policies by imposing the same cost on imports as if their production had taken place in the domestic country (Dissou and Eyland, 2011). Although most studies indicate that the distributional impact of a CT is likely to be regressive, disproportionate burdens on poor households can be offset by recycling some portion of the tax revenue back to them through direct rebates or targeted tax swaps (Morris and Munnings, 2013; Metcalf, 2009). Moreover, the revenue raised from a CT can be used to alleviate concerns over the environmental effectiveness of the tax through earmarking

[8]To date, 13 countries (i.e., Australia, Costa Rica, Denmark, Finland, France, Iceland, Ireland, Japan, Mexico, Norway, Sweden, Switzerland, and the United Kingdom) and one sub-national jurisdiction (i.e., British Colombia) have implemented a CT (http://www.carbontax.org/services/where-carbon-is-taxed/). Baranzini and Carattini (2013) review the main characteristics of carbon taxes and survey the environmental effectiveness of existing carbon taxes by focusing on empirical studies based on real data.

revenues for environmental purposes, thereby increasing the public acceptability (Dresner et al., 2006). It is worth noting that carbon taxation is gaining ground in developing countries. South Korea and Chile are planning to introduce a CT. Mexico and Costa Rica have already introduced it. Most recently, South Africa's carbon tax is scheduled to go into effect in January 2016 (World Bank, 2014).

The CE data come from 1252 individuals randomly selected from 16 cities of Turkey. To explore heterogeneity in public preferences for CT attributes, we analyze the data with the mixed logit (ML) and the latent class (LC) models. Although these two models incorporate heterogeneity in preferences in alternative ways, the results from both models indicate that there is significant heterogeneity in public preferences across our sample. The CT is characterized by the following four attributes: private cost, the distribution of the cost in society, the use of additional revenues, and raising awareness towards climate change. The results from the ML model suggest that the private cost has a negative effect on the probability of choosing the CT. Respondents prefer the CT with a progressive cost distribution rather than one with a regressive cost distribution. Earmarking revenues increases the probability of the tax being chosen. Moreover, respondents prefer the CT that raises public awareness about climate change. The marginal WTP calculations provide evidence that the most valued CT attribute is the use of additional revenues, followed by the distribution of the cost, and raising awareness towards climate change, respectively.

The LC model accommodates preference heterogeneity at the group level and sorts respondents into two segments based on their socioeconomic and attitudinal characteristics. Respondents in the first segment are more educated, more likely to be employed, and have higher levels of environmental consciousness compared to those in the second segment. In both segments, the CT with a progressive cost distribution is preferred to one with a regressive cost distribution, and respondents prefer the CT that promotes public awareness of climate change. As expected, the members of the first segment prefer earmarking for environmental measures over allocating CT revenues to the general government budget whereas the members of the second segment, who belong to lower socioeconomic groups, prefer the CT whose revenues are earmarked for income redistribution rather than used to fund the general government budget.

This study is organized as follows. The next section provides information about the CE design and data collection. Section 3 introduces the econometric models that account for heterogeneity in public preferences for CT attributes. Section 4 presents results and Section 5 concludes.

2 Choice Experiment Design and Data Collection

2.1 Choice Experiment Design

Economic methods for eliciting individuals' preferences can be divided into two groups. Revealed preference methods examine individuals' preferences based on their actions in real markets while stated preference methods involve asking individuals to state their preferences over hypothetical alternative scenarios. The CE, initially proposed by Louviere and Woodworth (1983) and Louviere and Hensher (1983), belongs to the group of stated preference methods.[9] In a CE, respondents are asked to undertake a sequence of choice tasks with two or more alternatives. Each alternative in a choice set is described by several attributes that consist of a number of levels. The variation across the alternatives in the choice sets is achieved by assigning different levels to the attributes.

In our CE, we asked respondents to choose between two CTs characterized by certain attributes and levels, as presented in Table 1. The following four attributes characterize CTs: private cost, the distribution of the cost in society, the use of additional revenues, and raising awareness towards climate change. The first attribute, private cost, represents

[9] The major drawback of the stated preference methods is their hypothetical nature. People may not know what they would do if a hypothetical situation was real or they may not be willing to reveal their true preferences. In addition, the respondent's perception of what the interviewer expects as answers may influence what the respondent says she will do (Train, 2009).

the cost of the CT that individuals incur per month. We include the cost attribute to be able to estimate welfare changes. The level of the cost takes one of three possible values: 2 Turkish lira (TL), 4 TL, and 6 TL.[10] The second attribute represents the distribution of the cost in society. The cost can be distributed across society in three possible ways: regressive, neutral, and progressive. If it is designed in a regressive way, each individual pays the same amount regardless of their income level. Such a distribution causes lower-income people to pay a larger share of their income than higher-income people pay. If the cost is imposed in a neutral way, all individuals pay the same percentage of their income. The progressive way of distributing the cost requires higher-income people to pay a larger percentage of their income, thereby favoring the poor. The third attribute represents the use of additional revenues generated from the implementation of the CT. The revenues can be allocated to the general government budget. In this case, the revenues could alleviate a budget deficit, providing room for discretionary increases in government spending. Alternatively, the revenues may be earmarked either for income redistribution or for environmental policies such as encouraging green innovation and tackling air pollution. Earmarking for income redistribution aims to support low-income households by lowering their income tax rate. Earmarking revenues can increase public acceptability of policy instruments due to distrust about government spending of revenues (Saelen and Kallbekken, 2011; Kallbekken and Saelen, 2011). However, earmarking may also create inflexibility and inefficiency. Fixing the use of revenue in advance

[10] Ideally, the CT rate has to reflect the marginal external damage costs of carbon emissions. Unfortunately, the precise estimates of these costs do not exist due to the difficulty in quantifying all the impacts of climate change on society. Several studies have attempted to calculate the marginal damages of carbon emissions. The IPCC (2007) indicates that the estimates of the social cost of carbon range from $3 to $95 per ton CO_2. Stern (2007) estimates an optimal tax rate of $ 85 per ton CO_2. Using the RICE-2011 model, Nordhaus (2011) find that the estimated social cost of carbon in 2015 is $44 per ton CO_2. There is no consensus in the literature about the optimal tax rate as the estimates of the social cost of carbon are widely divergent. The tax rates we proposed in this study are very modest for the following reasons. First, energy-related taxes in Turkey, which are levied mainly on the transport sector, are already high. Turkey levies an 18% value-added tax on all energy products. Moreover, a special consumption tax is levied on motor vehicle fuels, which causes Turkey to have the highest prices for gasoline, diesel, and LPG among OECD countries. Erdogdu (2014) finds that the income elasticity of gasoline is 0.132 (0.298) in the short (long) run in Turkey. Second, as pointed out by Godal and Holtsmark (2001) and Baranzini and Carattini (2013), introducing the tax at a modest level initially and allowing for incremental increases over time may promote the public acceptability of the tax as the phase-in approach provides time for emitters to adjust their behavior to avoid emissions.

might lead to obstacles to a reevaluation based on the economic and environmental rationale of a programme financed by earmarked revenues, causing inefficient spending of government revenue (OECD, 2001). Climate policies may encourage people to adopt more climate-friendly behaviors and help raise public awareness of climate change. Thus, the last attribute attached to the CT is whether it has a positive impact on raising awareness towards climate change.

In the CE, three attributes with three levels and one attribute with two levels lead to 54 alternatives and 1431 possible pairwise choices. Using Sawtooth Software, we employ complete enumeration as a design strategy to create six versions of our questionnaire, each containing 12 choice sets. The complete enumeration produces the most nearly orthogonal design. The orthogonality criterion requires that the levels of each attribute vary independently of each other so that each attribute level's effect may be estimated independently of all other effects. This design strategy also attempts to keep the alternatives within each choice set as different as possible. For example, if an attribute's number of levels equals the number of alternatives in a choice set, each level appears exactly once. Moreover, complete enumeration conforms to the level balance principle that requires all levels of each attribute to appear with equal frequency across alternatives (Sawtooth, 2010).

2.2 Choice Experiment Data Collection

The CE data were collected through face-to-face interviews made in January 2012. The survey was conducted with 1252 individuals who were randomly sampled from the residents of 16 cities in Turkey. The questionnaire was pilot tested to make sure that people fully understand the questions and concepts.[11] The final questionnaire consists of three main

[11] Face-to-face interviews took place in the respondent's home. We trained the interviewers to ensure that they had knowledge of the subject matter and understood the attributes and levels used in the CE very well. The interviewers provided the respondents with a 5-7 minute information session regarding the attributes and levels before presenting 12 CE questions. In order to reduce the well-known 'interviewer effect', we distributed to the interviewers a standardized text that was read out verbatim and in its entirety during the information session. Taking advantage of the face-to-face interviews, we did not allow the respondents to skip the CE questions. In the pilot study, we realized that respondents had difficulty in understanding the

parts. The first part provides data on the respondents' social and economic characteristics. The descriptive statistics presented in Table 3 reveal that half of the respondents are male. The average age of the respondents is 38. Roughly half of the respondents are located in one of the three major cities in Turkey; that is, Istanbul, Ankara, and Izmir. Respondents with a tertiary education make up almost 12 percent of the sample while nearly 6 percent of the respondents have no formal education. Roughly 44 percent of the respondents work as full-time or part-time employees. Married respondents account for 71 percent of the sample and approximately 69 percent have children. The second part of the questionnaire constitutes questions eliciting respondents' attitudes and awareness about environmental issues. We make use of the following four questions to construct an environmental awareness index (EAI): i) Are you a member of an environmental organization? (Yes=1, No=0); ii) Have you attended an event organized by an environmental organization? (Yes=1, No=0); iii) Have you ever heard of climate change? (Yes=1, No=0); iv) Do you agree with the following statement: 'My actions can make a difference to slow down climate change'? (Strongly Disagree=1, Somewhat Disagree=2, Somewhat Agree=3, Strongly Agree=4).[12] We calculate the index by simply summing the responses to these four attitudinal questions. The EAI ranges from 1 to 7, with higher values indicating that the respondent has more pro-environmental attitudes and actions. The average value of the index in the sample is 3.91 with a standard deviation of 1.25.

The third part in the questionnaire contains 12 CE questions. An example of a choice task that respondents faced in our survey is presented in Table 2. Before asking respondents CE questions, the interviewer described the attributes and their levels thoroughly and clearly.

levels of the attribute for the distribution of the cost in society due to problems with the wording. To improve comprehension, we simplified complicated sentences and reworded the text to explain to the respondents the three levels assigned to this attribute. The English translation of the original questionnaire is presented in the Appendix.

[12] After examining 128 pro-environmental behaviour research studies, Hines et al. (1986) point out that an individual's perception of whether they have the ability to bring about change through their own behaviour, which is called locus of control in the literature, is one of the six variables associated with responsible pro-environmental behaviour. For example, people with a strong internal locus of control might believe that their recycling behaviors can create positive environmental change, thereby increasing their propensity to recycle.

The respondents were also informed that there were no right or wrong answers, we were just interested in their preferences/opinions.

Table 3 compares the socioeconomic characteristics of the sample with those of the Turkish population. The sample seems to be representative of the Turkish population living in urban areas. However, two important differences are that our sample is more educated and has a higher proportion of respondents living in one of the three major cities in Turkey. To reconcile these differences between the sample and the population, we compute three different post-stratification weights using the information provided in Table 3. First, we compute weights that bring the sample distribution into line with the population in terms of education level. Second, we compute weights based on the distribution of the place of residence.[13] Third, to incorporate the post-stratification adjustment for education and place of residence, we also use the average of these two weights as previously computed. As post-stratification weighting does not result in any significant changes in the estimates, we report and interpret the unweighted estimates in Section 4.

3 Econometric Model

In addition to the standard logit model, we employ the ML model and the LC model to analyze the CE data. The ML model overcomes three drawbacks of the standard logit model by allowing for heterogeneity in tastes, correlation in unobserved factors over repeated choices by each individual, and complete relaxation of the independence of irrelevant alternatives (IIA) property (Train, 1998). The utility that the individual i derives from choosing alter-

[13]We utilize the following formula to compute a weight for the respondent i: $W_i = \frac{P_p}{P_s}$ where P_p is the population proportion and P_s is the sample population. When we use education level as our post-stratifying variable, the weight applied to individuals with no formal education is $\frac{0.086}{0.056} = 1.522$; the weight applied to individuals with primary education is $\frac{0.297}{0.366} = 0.811$; and so on. Likewise, when we use place of residence as our post-stratifying variable, the weight applied to individuals who live in one of the three major cities in Turkey is $\frac{0.372}{0.513} = 0.725$ while the weight applied to the others is $\frac{0.627}{0.487} = 1.287$.

native j in choice set t can be defined as

$$U_{ijt} = X'_{ijt}\beta_i + \epsilon_{ijt}, \quad j = 1, 2, .., J, \quad i = 1, 2, ..., n, \quad t = 1, 2, .., T \tag{1}$$

where X_{ijt} is the vector of explanatory variables, including the attributes of the alternatives, and ϵ_{ijt} is a random error term. In the ML model, the parameters (β_i) that vary randomly across individuals can be decomposed into two parts:

$$\beta_i = b + \eta_i, \quad i = 1, 2, ..., n \tag{2}$$

where b is the mean of the parameter and η_i is a random term that represents unobserved deviations from the mean b. The utility function then becomes:

$$U_{ijt} = X'_{ijt}b + X'_{ijt}\eta_i + \epsilon_{ijt} \tag{3}$$

The fact that η_i varies randomly across individuals allows for heterogeneity in tastes. Since η_i is allowed to be correlated across alternatives and choice sets, the ML model is not subject to IIA assumption and incorporates the panel structure of the data. It is important to note that if η_i was zero, β_i would be known for each individual and we would obtain the standard logit model. Under the assumption that ϵ_{ijt} is independently and identically distributed with type I extreme value distribution, the conditional probability that each individual makes a particular sequence of choices d=d_1,d_2,..,d_T equals the product of the conditional logit probabilities for each choice:

$$L_{id}(\beta) = \prod_{t=1}^{T} \frac{exp(X'_{ijt}\beta_i)}{\sum_{j=1}^{J} exp(X'_{ijt}\beta_i)} \tag{4}$$

As β is unknown, the unconditional probability for a sequence of choices can be expressed by integrating over all values of β weighted by the density of its distribution:

$$P_{id} = \int L_{id}(\beta) f(\beta) d\beta \tag{5}$$

where $f(\beta)$ denotes the density of each parameter. In the ML model, each random parameter can take on different distributional forms such as normal, lognormal, uniform, or triangular. We assume that all the parameters except the cost attribute follow a normal distribution; that is, $f(\beta)\sim$ N(μ,σ^2) where μ and σ are parameters to be estimated in the model.[14] The parameter of the cost attribute is treated as a non-random (fixed) parameter. Sillano and Ortúzar (2005) point out that when all coefficients vary across the population, the ML model tends to be unstable, causing some identification issues to arise. Moreover, fixing the cost parameter allows us to easily derive the marginal WTP estimates.[15] The integral in (5) is estimated with simulated maximum likelihood estimation using Halton draws.

Unlike the ML model that captures heterogeneity at the individual level, the LC model accommodates preference heterogeneity at the segment (or group) level.[16] The LC model can be interpreted as a semiparametric version of the ML model because the analyst does not need to make any distributional assumptions on the distributions of the random parameters (Greene and Hensher, 2003). The rationale behind the LC model is based on the idea that the population can be sorted into a finite and identifiable number of groups of individuals (i.e., segments). Within each segment, individuals are relatively homogeneous with respect to their preferences. However, across segments, they have heterogeneous pref-

[14] Any probability density function can be specified for the distribution of the parameters in the population. Selecting such a distribution presents a challenge given the unknown distribution of parameters. Applying Monte Carlo simulation methods, Torres et al. (2011) provide evidence that the bias resulting from imposing a wrong distribution on the random parameters is smaller than the bias due to the incorrect assumption that preferences are homogeneous.

[15] In a model with a fixed cost parameter β_c and an attribute whose parameter is normally distributed with mean μ and standard deviation σ (i.e., $\beta_{attribute} \sim N(\mu, \sigma)$), the resulting WTP distribution for the attribute is given by : $\frac{\beta_{attribute}}{\beta_c} \sim N(\frac{\mu}{\beta_c}, \frac{\sigma}{\beta_c})$

[16] See Colombo et al. (2009) for a detailed comparison of these two models on the basis of accounting for preference heterogeneity in CEs.

erences. The LC model incorporates heterogeneity across individuals by identifying latent individual segments with heterogeneous preferences. In the LC model, each individual is assigned into a specific segment that is probabilistically based on the individual's socioeconomic background, perceptions, and attitudes. Moreover, individual characteristics affect choices indirectly through the segment membership function rather than directly through the utility function. The choice probability that individual i in segment s chooses alternative j in choice set t is expressed as:

$$P_{it|s}(j) = \frac{exp(X'_{it,j}\beta_s)}{\sum_{j=1}^{J} exp(X'_{it,j}\beta_s)}, \quad s = 1, 2, ..., S \tag{6}$$

where β_s is a vector of segment-specific utility parameters to be estimated. If each individual i faces T choice situations that are assumed to be independent, the contribution of individual i to the likelihood for the given segment assignment is:

$$P_{i|s} = \prod_{t=1}^{T} P_{it|s} \tag{7}$$

In contrast to the ML model, the LC model assumes that unobserved factors are independent across the choice sets faced by a single individual, thereby failing to control for the panel nature of the data. Following Swait (1994), we construct an unobservable or latent segment membership likelihood function in equation 8 that sorts individuals into one of the S segments with some probability P_{is}

$$H^*_{is} = M'_i\delta_i + \zeta_{is} \tag{8}$$

where M_i denotes a set of observable characteristics of the individual that influence segment membership and δ_i represents segment membership parameters. Under the assumption that the error terms in equation 8 are independently and identically distributed across individuals and segments and follow a type I extreme value (Gumbel) distribution, the probability that individual i belongs to segment S is characterized by:

$$P_{is} = \frac{exp(M_i'\delta_s)}{\sum_{s=1}^{S} exp(M_i'\delta_s)}, \quad s = 1, 2, ...S, \quad \delta_S = 0 \tag{9}$$

The segment membership parameters for segment S (δ_S) must be normalized to zero to identify segment membership parameters for the other segments. The individual i's contribution to the likelihood function is given by:

$$P_i = \sum_{s=1}^{S} P_{is} * P_{i|s} \tag{10}$$

The log likelihood function for the sample consisting of N individuals is:

$$lnL = \sum_{i=1}^{N} ln[\sum_{s=1}^{S} P_{is} * (\prod_{t=1}^{T} P_{it|s})] \tag{11}$$

4 Empirical Results

4.1 Mixed Logit

In addition to the standard logit model, we estimate the ML model to account for unobserved heterogeneity in the data.[17] We use 200 Halton draws to estimate each of the random parameters. Table 4 presents estimation results from the standard logit and the ML model. We use the log likelihood ratio test to determine whether the standard logit is outperformed by the ML model. Comparing the test-statistic to the chi-square critical value of 11.07, we conclude that the ML model is significantly better than the standard logit model.[18] The ML model has a higher overall fit compared to the standard logit model with a pseudo R^2

[17]The choice data were analyzed using LIMDEP/NLOGIT 4.0

[18]The log likelihood ratio (LLR) test =-2($lnL_r - lnL_u$) where L_r is the log likelihood of the restricted model and L_u is the log likelihood of the unrestricted model. It follows chi-square distribution with degrees of freedom equal to the difference between the number of parameters estimated between the two models. If the value of the LLR test exceeds the critical chi-squared value, then the null hypothesis, that the standard logit and the ML model are the same, is rejected.

of 0.10.[19]

The ML model estimation results indicate that all the mean parameter estimates are statistically significant at the 1 percent level.[20] The signs of parameter estimates are consistent with those in the standard logit model. Respondents express a strong preference for earmarking tax revenues. Several studies indicate that how the revenue of an environmental tax is used matters, and earmarking the revenue increases public support (see e.g., Steg et al., 2006; Kallbekken and Aasen, 2010; Saelen and Kallbekken, 2011). Public distrust in governments may be the reason why earmarking increases the public acceptability of CTs.[21] After examining the attitudes of the general public about the ecological tax reform policies in Europe, Dresner et al. (2006) find that people believe environmental taxes are used only to raise revenue for the government rather than to address environmental objectives. If people are concerned about the environmental effectiveness of the CT, then earmarking revenues for environmental purposes, which links taxation and spending to the same domain, may lead to a substantial increase in the public acceptability.

We find that respondents prefer a CT that raises awareness towards climate change. This result may suggest that governments can increase public support for a CT by providing individuals with education and information regarding the effectiveness of a CT in tackling climate change. Wider publicity strengthening the message that a CT leads to positive

[19]The pseudo R^2 of a choice model is not exactly the same as the R^2 of a linear regression. The pseudo R^2 values tend to be much lower. Hensher and Johnson (1981) state that the values of the pseudo R^2 between 0.2 and 0.4 are considered as an extremely good fit of the data in choice analysis.

[20]All the attributes presented in Table 1, except for the cost attribute, enter the utility function as categorical variables. We create effects coded variables representing those attributes. The base level of each attribute is 'regressive', 'no', and 'general fund revenue', respectively. Effects coding allows for non-linear effects to be measured in the levels of the attributes (Hensher et al., 2005). The cost attribute is included as a continuous variable.

[21]Under the International Social Survey Programme (ISSP) 2010, 45,000 individuals from 32 countries were interviewed about their attitudes towards environmental issues, their preferences for governmental measures on environmental protection and their trust in their government. Using data from the ISSP 2010, Kollmann and Reichl (2015) investigate the impact of people's trust in their government on their willingness to accept higher environmental taxes. They calculate the percentage of people who trust their government very strongly or strongly in each country. Their calculations indicate that Switzerland has the highest trust level (50 percent) while Latvia and Lithuania have the lowest levels (6 percent) among European countries. The trust level for Turkey is reported as 36 percent. Kollmann and Reichl (2015) provide evidence that political trust has a significant positive impact on the public acceptance of environmental taxes.

environmental consequences might help not only raise public awareness on climate change issues but also reduce resistance to the introduction of a CT. However, Kahan et al. (2011) point to the complexity behind the reasons for skepticism about climate change. They show that the perception of environmental risks that climate change poses to human health and prosperity is primarily associated with value systems rather than scientific literacy. An increase in scientific literacy does not cause polarization of climate risk perception to decrease. Cultural factors plays an important role in determining climate risk perception. Moreover, Cohen and Viscusi (2012) assess the effectiveness of the utilization of informational approaches in the context of climate change policies, such as information disclosure and warnings. They underscore that the design of information policies is crucial; unless they are properly crafted, they yield little reduction in GHG emissions.

Given that potential candidates for disseminating information about the role of a CT in tackling climate change include the research community and nongovernmental organizations (NGOs), a close collaboration with such civil society organisations might be considered as an essential element of designing a CT that raises public awareness on climate change issues.[22] In addition, the government should make effective use of the Internet and social media to communicate climate science and promote low carbon lifestyles when introducing a CT as a climate change policy instrument.

The results indicate that respondents are more likely to choose the CT with a progressive-like cost distribution. Unless accommodations are made, a CT is likely to be regressive as low-income households spend a higher percentage of their income on energy than high-income households. Fullerton (2011), studying six different types of distributional effects of a CT, concludes that all the effects may place a disproportionate burden on the poor. However, recent studies analyzing the general equilibrium effects of a CT suggest that a CT may be progressive even before using tax revenues to compensate for the losses of low-income families

[22]The TEMA Foundation, which is the first environmental NGO in Turkey accredited as an observer to the UNFCCC, has played a very active role in raising environmental awareness in Turkey (see http://tema.org.tr for more information).

(Beck et al., 2015; Dissou and Siddiqui, 2014; Hassett et al., 2009).[23] For example, Dissou and Siddiqui (2014) assess the distributional incidence of CTs by taking into account changes in both commodity and factor prices. They show that the effect of changes in commodity prices works in the opposite direction to the effect of changes in factor prices and CTs tend to be progressive through the changes in factor prices. Even if negative distributional impacts do arise, they can be counteracted through the use of tax revenues to favor low-income households directly or indirectly. There are a number of options for policymakers to recycle the revenue back to vulnerable households through direct rebates and tax swaps (Metcalf, 2009; Dinan, 2012; Morris and Munnings, 2013). In addition, the CT design that incorporates tax-free thresholds can take into account the possible distributional inequity of a CT. For example, a CT that sets a tax-free allowance for the essential use of energy such that the tax is only paid on consumption above the allowance would reduce the adverse distributional effects on lower-income households (Zhang and Baranzini, 2004 ; Pezzey and Jotzo, 2013; Bristow et al., 2010). Alternatively, a hybrid design combining an efficient revenue recycling with tax-free thresholds can be implemented to mitigate the regressive distributional impacts. In sum, our results suggest that it is crucial for policymakers to gain a good understanding of what makes a CT regressive or progressive and how low-income households can be effectively compensated for the negative impacts of a CT.[24]

Consistent with economic theory, the private cost has a negative effect on the probability of choosing the CT. Brannlund and Persson (2012) also find that the private cost is negatively related to the choice of a CT in Sweden. Saelen and Kallbekken (2011) show that individuals on average prefer lower fuel taxes in Norway. On the other hand, Bristow et al. (2010) provide

[23]Shah and Larsen (1992) argue that the regressivity of a CT is likely to be less pronounced in a developing country than in a developed country because the former may differ from the latter in the institutional factors that affect the incidence of a CT. Using a computable general equilibrium model, Yusuf and Resosudarmo (2015) examine the distributional impact of a CT in Indonesia. They provide evidence that the introduction of a CT in Indonesia tends to be progressive.

[24]A 'progressive' random parameter has a correlation of 0.30 with 'earmarking for income redistribution'. Given that these random parameters are statistically significant, the low degree of correlation between them suggests that as an alternative to designing progressive-like cost distribution, using the revenues to correct for the negative distributional impacts on low-income households would also improve the public acceptability of a CT.

evidence that the impact of the CT rate on CT acceptability varies considerably, especially among high carbon consumers. Moreover, in reviewing the literature on the acceptability of road pricing schemes, Jaensiriak et al. (2005) point out that the findings on the effect of the level of the charge on the acceptability of the charge are not conclusive across the studies undertaken.

Statistically significant parameter estimates for derived standard deviations of a random parameter indicate the presence of heterogeneity in the parameter estimates across the sample population around the mean estimate, whereas insignificant parameter estimates suggest that the dispersion around the mean is statistically equal to zero, implying that all information in the distribution is captured within the mean. The third column of Table 4 shows that 'progressive' and 'earmarking for environmental policies' have statistically significant parameter estimates for derived standard deviation, suggesting that different individuals have individual-specific parameter estimates that may differ from the mean parameter estimate for the sample population. On the other hand, the insignificant parameter estimates for derived standard deviation of 'neutral', 'raising awareness of climate change', and 'earmarking for income redistribution' suggest that all information about these parameters is explained solely by the mean of the sample population parameter.[25]

The coefficient estimates of the standard logit and ML models can be used to estimate welfare measures in the form of marginal WTP. Marginal WTP estimates represent the marginal rate of substitution between the change in a given CT attribute and the marginal utility of money denoted by the coefficient of the cost attribute. The last two columns of Table 4 show the marginal WTP estimates for the standard logit and ML models.[26] All the marginal WTP estimates are statistically significant at the 1 percent level. The pair-wise t-tests indicate that the marginal WTP estimates for all attributes differ significantly at the 1

[25]To check the robustness of our results, we estimate a model where all the random parameters are specified to have triangular distributions. The triangular distribution does not impose symmetry and is restricted on both sides. The results are robust to this change in the distributional assumption. Moreover, we re-estimate the model where random parameters with insignificant standard deviation estimates are treated as non-random parameters with a greater number of draws. We confirm stability in the results.

[26]The marginal WTP values are estimated using the Wald procedure in LIMDEP 9.0 and NLOGIT 4.0.

percent level between these two models. Given that the ML model outperforms the standard logit model, we interpret the marginal WTP estimates based on the ML model. The marginal WTP estimates provide insights on the relative importance of each CT attribute. The most valued CT attribute is the use of additional revenues followed by the distribution of the cost, and raising awareness towards climate change, respectively. The respondents appear to be particularly sensitive to the use of additional revenues generated from the implementation of the CT and show a strong preference for earmarking, suggesting that there is significant distrust of how the government will spend the tax revenue. The marginal WTP estimates indicate that earmarking revenues for environmental purposes is valued more than that for income redistribution. High marginal WTP estimate for 'earmarking for environmental policies' may reflect respondents' concern over the environmental effectiveness of a CT, which can be alleviated by linking taxation and spending to the same activity. The results also show that Turkish people highly value a progressive-like cost distribution.

Because the ML estimation results indicate that the dispersions of the 'progressive' and 'earmarking for environmental policies' random parameters are statistically significant, we estimate the ML model with interactions to explore the sources of heterogeneity. After estimating a number of specifications that include the interactions of respondents' social, economic, and attitudinal characteristics with the 'progressive' and 'earmarking for environmental policies' attributes, we find that the model including the interactions of respondents' education, employment status, and the EAI with these two attributes fits the data the best. The results from the ML model with interactions, which are presented in Table 5, can be summarized as follows. First, the mean sample population parameter estimates, except for 'progressive' and 'earmarking for environmental policies', are statistically significant. Second, the interactions between the EAI and 'earmarking for environmental policies' and 'progressive' are positive and statistically significant, indicating that respondents with higher levels of environmental consciousness are likely to prefer the tax revenues to be earmarked for environmental purposes and that they tend to show a preference for progressive-like cost distribution. This finding may suggest that environmental consciousness is positively associated with concerns about the environmental effectiveness and equity of a CT. Third, the differences in the marginal utilities held for the 'earmarking for environmental policies' attribute can be partly explained by differences in respondents' employment status. Employed individuals are likely to prefer a CT whose revenues are earmarked for environmental measures. Fourth, in line with the ML model presented in Table 4, the ML model with interactions leads to significant derived standard deviations for the 'progressive' and 'earmarking for environmental policies' attributes, underlining the presence of preference heterogeneity. The log-likelihood ratio test statistic suggests that the ML model with interactions results in a statistically significant improvement in the model fit.

4.2 Latent Class Model

Following Louviere et al. (2000) and Andrews and Currim (2003), we use the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the pseudo R^2 to determine the optimal number of segments. Table 6 presents these statistics from an LC model where the number of segments ranges from one to five. The case in which there is only one segment corresponds to the standard logit model. As shown in Table 6, the log likelihood value improves and the pseudo R^2 increases as more segments are added to the model, indicating the existence of multiple segments in the sample. Although the AIC and BIC improve as the number of segments increases, the marginal improvement in the AIC and BIC diminishes after the two-segment model. Therefore, the two-segment LC model is selected as the best fit to the data.

Table 7 presents the results of the two-segment model. The top panel of Table 7 shows the utility parameter estimates for climate policy attributes while the bottom panel presents segment membership parameter estimates. The segment membership parameters for the second segment are normalized to zero to secure the identification of the model. Thus, segment membership parameter estimates are described relative to the normalized second segment.

After experimenting with different specifications, we include the respondents' education, employment status, and EAI as variables that affect segment membership. The results indicate that respondents in the first segment are more educated, have higher EAI values, and are more likely to be employed compared to those in the second segment.

The utility parameter estimates show that all the attribute level estimates, except for 'Neutral' in segment 1, are statistically significant at the 1 percent level. As expected, the private cost is negatively related to the probability of choosing a CT. However, the negative effect of the CT rate on the probability of choosing a CT is bigger in segment two than in segment one. The ranking of climate policy attributes differs between the two segments, indicating the existence of heterogeneity in preferences. In both segments, the CT with a progressive cost distribution is preferred to the one with a regressive cost distribution, suggesting that policymakers should take equity concerns into consideration to design a publicly acceptable CT. Respondents also prefer a CT that promotes public awareness of climate change. Members of the first segment prefer a CT whose revenues are earmarked for income redistribution to one whose revenues are used to fund the general government budget, whereas in the second segment earmarking revenues for income redistribution is preferred to the allocation of additional revenues to the general government budget. This finding is in line with the segment membership parameter estimates, indicating that respondents with higher EAI values are more likely to belong to the first segment and the second segment consists of individuals with lower socioeconomic status.

The marginal WTP estimates reported in the last two columns in the top panel of Table 7 vary considerably between the two segments, highlighting the importance of accounting for the heterogeneity of preferences across respondents. It is worth noting that the marginal WTP estimates for all attribute levels in segment 2, except for Neutral, are substantially lower than those in segment 1. This finding can be explained by several factors that lead to public opposition to a CT. For instance, segment 2 may consist of individuals who have serious doubts about a CT's ability to bring down carbon emissions. As a result, the perceived effectiveness of a CT may have an impact on the marginal WTP values. Examining public attitudes towards fuel taxation in Norway, Kallbekken and Saelen (2011) indicate that beliefs about environmental consequences of the tax, concerns about negative distributional impacts, and socio-political factors are important predictors of public support for the tax. In the questionnaire, we asked respondents what the government should implement as a primary policy instrument to address climate change. We find that highly educated people are more likely to favor environmental taxes as a primary policy instrument. For example, 13.6 percent of individuals with at least a university degree think that environmental taxes should be used as a primary policy instrument while this rate is 6.75 percent for those with only a primary education. Given that the segment membership parameter estimates show that segment two is more likely to comprise less educated individuals, the descriptive statistics reinforce our conjecture that CT dislike may be the reason for the significantly lower marginal WTP values in segment two. It would be interesting to explore the reasons behind public opposition to CTs. Do people understand the basic rationale for those taxes? Do they understand how the taxes increase welfare through the existence of a double dividend? Do they believe that the taxes are effective in altering behaviour? The limitations of the data do not allow us to answer these questions in the current study. We leave the exploration of these questions to future research.

After thoroughly reviewing the literature on the acceptability of climate change policies, Upham et al. (2009) point out that although incentive-based policies such as regulation and informational campaigns tend to be widely supported by the public, there is limited support for market-based policy instruments for mitigating climate change. Consistent with the literature, the answers to the question regarding which instrument should be implemented by the government to address climate change indicate that Turkish citizens prefer regulations and informational campaigns over environmental taxes.[27] There are probably

[27]Please see question 14 in the Appendix. The alternatives in the question and the percentage of the sample chosen for each alternative are as follows: (i) enacting environmental taxes (10%); (ii) organizing public campaigns that promote environmental consciousness (23%); (iii) enacting regulations that seek to protect the environment (39%); (iv) providing individuals and firms with subsidies for environmentally

several reasons for the lack of public support for a CT in the first place. First, investigating driving forces behind the unpopularity of Sweden's CT compared to other climate policy measures, Jagers and Hammar (2009) argue that people tend to be more supportive of alternative policy instruments such as subsidies and information campaigns due to a systematic lack of information that is available to the public about the social cost associated with these alternative policy instruments. The CT implies a visible cost on individuals' budget. However, people may disregard the fact that the alternative policy measures are not cost free. As suggested by Jagers and Hammar (2009), to increase the popularity of CTs policymakers should present the intended effects of such taxes on emissions and their private and social costs in connection with the alternatives. Second, previous research reveals that people are more positive towards environmental taxes if they trust their politicians and their co-citizens (Harring and Jagers, 2013; Hammar and Jagers, 2006; Kollmann and Reichl, 2015). According to the fifth wave of the World Value Survey (2004-2008), Turkey has an extremely low social trust level among the 57 countries in the survey. The proportion of Turkish people who say that 'most people can be trusted' is only 4.8 percent, which makes Turkey the second-lowest social trust country of the 57 countries surveyed. Ekmekci (2014) provides evidence that widespread interpersonal distrust in Turkey is closely associated with low political trust as well. In that respect, the transparency provided by earmarking can alleviate public opposition to environmental taxes to some extent. Third, respondents may already feel overtaxed due to the high consumption tax rates in Turkey (OECD, 2014).[28] If this is the case, emphasizing the possibility of framing a revenue-neutral CT may help the government to overcome the present unpopularity of CTs.

Finally, we compare the LC model to the ML model with interactions using a test proposed by Ben-Akiva and Swait (1986). The test rejects the null hypothesis that the ML

friendly activities (7%); (v) integrating climate change education into the school curriculum (16%); and (vi) no answer/do not know (5%).

[28]In Turkey consumption taxes produce 43.2 percent of total tax revenue, whereas the OECD average for the share of consumption taxes in the total tax revenue is 30.9 percent (OECD, 2014). The presence of a large informal economy and the simple administration of consumption taxes are among the reasons why Turkey favors consumption taxes over income taxes.

model with interactions is the true model. Therefore, we conclude that the LC model outperforms the ML model with interactions. Although these two models offer alternative ways of incorporating heterogeneity in preferences, the estimation results from both the LC model and the ML model with interactions highlight that there is significant heterogeneity in public preferences across our sample.

5 Conclusion

Climate change is one of the most urgent problems that the international community faces. The active participation of developing countries in mitigation efforts will be a crucial element of an effective global climate change framework. We conduct a choice experiment to investigate public preferences for carbon tax attributes in a developing country context. We find that all the attributes characterizing carbon taxes in the experiment significantly affect an individual's choice of a preferred carbon tax. Turkish people prefer carbon taxes with a progressive cost distribution rather than those with a regressive cost distribution. Earmarking carbon tax revenues increases the public acceptability of the tax. The private cost has a negative impact on the choice of the carbon tax. There is a preference for a carbon tax that promotes public awareness of climate change. We also find that the most valued carbon tax attribute is the use of the additional revenues, followed by the distribution of the cost, and raising awareness towards climate change, respectively. The adoption of an appropriate carbon tax is a viable option and deserves full consideration in addressing climate change. Our study provides valuable insights that researchers and policy makers can use to design an effective and publicly acceptable climate change policy.

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6 Appendix: The questionnaire

This appendix includes the English translation of the original questionnaire that consists of three parts, the first two of which contain questions prepared to ascertain the social and economic characteristics of the respondents and their attitudes towards and awareness of environmental issues. The third part contains the text explaining to the respondents the attributes and levels used in the CE. It is important to note that each question in parts 1 and 2 has the option of a ‘no answer’ (or ‘do not know’) response.

PART I

1- What is your age?

2- What is your gender?

•Female

•Male

3- What is the highest level or degree of schooling you have completed?

•No schooling completed

•Primary school

•Lower secondary school

•High school

•University degree

•Master’s degree

•Doctorate degree

4- What is your marital status?

•Married

•Single

5- Do you have children?

•Yes

•No

6- What is your employment status?

•Full-time employed

•Part-time employed

•Self-employed

•Housewife

•Student

•Retired

•Not employed

•Unable to work

7- What is your monthly household income?

•Less than 500 TL

•501 TL to 1,000 TL

•1,001 TL to 1,500 TL

•1,501 TL to 2,000 TL

•2,001 TL to 2,500 TL

•2,501 TL to 3,000 TL

•3,001 TL or more

<u>PART II</u>

8- Are you a member of an environmental organization?

•Yes

•No

9- Have you attended an event organized by an environmental organization?

•Yes

•No

10- To what extent are you concerned about environmental problems?

•Not concerned at all

•A little concerned

•Somewhat concerned

•Very concerned

11- Which of the following should play a more active role in environmental protection?

•Government

•Municipalities

•Individuals

•Firms

•Environmental organizations/NGOs

12- Have you heard of the problem of climate change?

•Yes

•No

13- Who do you think is mainly responsible for climate change?

•Government

•Municipalities

•Private sector

•Individuals

14- Which of the following should be implemented by the government as a primary policy instrument to address climate change?

•Enacting environmental taxes

•Organizing public campaigns that promote environmental consciousness

•Enacting regulations that seek to protect the environment

•Providing individuals and firms with subsidies for environmentally friendly activities

•Integrating climate change education into the school curriculum

15- To what extent do you agree with the following statement:'My actions make a difference to slowing down climate change'?

•Strongly disagree

•Somewhat disagree

•Somewhat agree

•Strongly agree

PART III

The increased concentration of greenhouse gas emissions in the atmosphere from human activities is the main cause of global warming and climate change. Climate change is one of the major challenges facing the world. Unless addressed, the impacts of climate change can be very severe, such as life-threatening floods and droughts and lack of food security, and may eventually lead to the forced migration of millions around the world. Government intervention is inevitable to address climate change. The government can tackle climate change by using various policy instruments such as regulations, campaigns, and carbon taxes. In recent years, the use of carbon taxes has been widely debated by economists as an effective and efficient policy instrument.

In the next twelve questions, we ask you to choose between the two carbon taxes that are characterized by the following attributes and levels.

Attribute 1: **Distribution of the cost in society:**

Cutting greenhouse gas emissions imposes a cost on society. This cost can be distributed across society in three possible ways:

(a) **Regressive**: All citizens pay the same amount regardless of their income level.

(b) **Neutral**: All citizens pay the same percentage of their income. For example, all citizens pay 1% of their income.

(c) **Progressive**: Higher-income citizens pay a higher percentage of their income while lower-income citizens pay a lower percentage of their income. For example, higher-income citizens pay 3% of their income but lower-income citizens pay 1% of their income.

Attribute 2: **Raising awareness of climate change:**

A carbon tax may affect people's awareness about climate change, which would, in turn, promote the adoption of more climate-friendly behaviors.

(a) **Yes**, A carbon tax raises climate awareness among Turkish people

(b) **No**, A carbon tax does not raise climate awareness among Turkish people.

Attribute 3: **Use of additional revenue:**

The government raises money by imposing a carbon tax. These additional revenues can be used in three different ways.

(a) **General fund revenue**: The revenues are allocated to the government budget to cover the government's general expenses

(b) **Earmarking for income redistribution**: The revenues are used to support low-income households by lowering their income tax rate

(c) **Earmarking for environmental policies**: The revenues are used for environmental measures such as subsidizing investments in clean infrastructure and green innovation or for tackling air pollution.

Attribute 4: **Private cost**:

Cutting greenhouse gas emissions imposes a cost on society. Therefore, depending on the choice of carbon tax, you incur the cost in some way per month. The level of the cost takes one of the three possible values.

(a) **2 TL**

(b) **4 TL**

(c) **6 TL**

In this part of the questionnaire you are presented with 12 choice cards. In each case, you will be asked to choose between two carbon taxes (labeled '**Carbon Tax A**' and '**Carbon Tax B**') that differ only in terms of the aforementioned attributes and levels. There are no right or wrong answers, we are just interested in your preferences/opinions. Even if you do not like any of the carbon taxes, please choose the one you most prefer.

Table 1

Carbon tax attributes and their levels

Attribute	Definition	Levels
Distribution of the cost in society	Carbon tax designed to reduce CO_2 emissions will impose a cost on society, which can be distributed across society in different levels.	• Regressive • Neutral • Progressive
Raising awareness towards climate change	Carbon tax may make people change their behavior to be more climate friendly.	• Yes • No
Use of additional revenues	The government raises money by implementing a carbon tax. These additional revenues can be used in three different ways.	• General fund revenue • Earmarking for income redistribution • Earmarking for environmental policies
Private cost	The cost of the carbon tax individuals incur (monthly).	• 2 TL • 4 TL • 6 TL

Table 2
An example of a choice set

All else being equal, which alternative would you prefer?		
	Carbon Tax A	**Carbon Tax B**
Distribution of the cost in society	Regressive	Neutral
Raising awareness towards climate change	Yes	No
Use of additional revenues	Earmarking for environmental policies	General fund revenue
Private cost	6 TL	2 TL
I would prefer (tick your choice)	[ ]	[ ]

Table 3

Descriptive statistics

Variable	**Description**	**Sample Statistics**	**Population Statistics**
Gender	binary variable,=1 if the respondent is male	49.9%	50.23%
Age	Age of the respondent in years	37.45(12.23)	37.78
Employment	Binary variable,=1 if the respondent is employed (full-time or part-time employment)	43.7%	41.65%
No education	Binary variable,=1 if the respondent has no formal education	5.67%	8.63%
Primary education	Binary variable,=1 if the respondent's highest level of education is primary education	36.6%	29.74%
Lower secondary education	Binary variable,=1 if the respondent's highest level of education is lower secondary education	15.2%	22.67%
Higher secondary education	Binary variable,=1 if the respondent is a high school graduate	30.7%	25.97%
Tertiary education	Binary variable,=1 if the respondent has at least a university degree	11.8%	12.99%
Married	Binary variable,=1 if the respondent is married	71.3%	73.38%
Children	Binary variable,=1 if the respondent has children	68.6 %	-
Environmental awareness index (EAI)	It is based on questions measuring respondents' environmental attitudes and awareness and ranges from 1 to 7	3.91(1.25)	-
Big city	binary variable,=1 if the respondent lives in one of the three major cities in Turkey, namely Istanbul, Ankara and Izmir, and =0 if the respondent lives in one of the following cities: Adana, Antalya, Bursa, Diyarbakir, Erzurum, Gaziantep, Kayseri, Konya, Malatya, Manisa, Samsun, Tekirdag, or Trabzon	51.3%	37.29%

Notes: All the population statistics except the employment variable come from the 2011 Turkish Statistical Institute (TURKSTAT) Population Statistics for individuals between 18 and 65 years of age. The population statistics on the employment variable are obtained from the TURKSTAT Household Labor Survey for December 2011. The numbers in the parentheses are the standard deviations.

Table 4

Standard logit and mixed logit model estimates for carbon tax attributes

	Standard Logit	Mixed Logit		Marginal WTP	
	Coefficient	**Mean**	**Std.Deviation**	**Standard Logit**	**Mixed Logit**
Neutral	0.082***	0.055***	0.304	0.327***	0.249***
	(0.017)	(0.019)	(0.257)	(0.068)	(0.078)
Progressive	0.214***	0.195***	0.472***	0.849***	0.877***
	(0.017)	(0.035)	(0.194)	(0.072)	(0.083)
Raising awareness towards climate change	0.235***	0.145***	0.225	0.934***	0.653***
	(0.012)	(0.025)	(0.414)	(0.055)	(0.055)
Earmarking for income redistribution	0.043***	0.056***	0.032	0.173***	0.251***
	(0.016)	(0.019)	(0.268)	(0.067)	(0.076)
Earmarking for environmental policies	0.529***	0.470***	0.404**	2.100***	2.112***
	(0.017)	(0.078)	(0.205)	(0.089)	(0.120)
Cost	−0.252***	−0.222***	-	-	-
	(0.007)	(0.036)			
Log-likelihood	-19293.27	-9362.59			
Pseudo R^2	0.073	0.100			
Log likelihood ratio test statistic	20849.28				
Number of respondents	1252	1252			
Number of observations	15024	15024			

Notes: ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses. The base level of each attribute is ‘regressive’, ‘no’, ‘general fund revenue’, respectively.

Table 5

Mixed logit with interactions model estimates for carbon tax attributes

	Mean	Std.Deviation	Marginal WTP
Neutral	0.057**	0.254	0.253***
	(0.022)	(0.284)	(0.077)
Progressive	-0.040	0.475**	-0.177
	(0.052)	(0.216)	(0.229)
Raising awareness towards climate change	0.149***	0.277	0.659***
	(0.044)	(0.727)	(0.055)
Earmarking for income redistribution	0.056**	0.010	0.249***
	(0.023)	(0.264)	0.076
Earmarking for environmental policies	-0.091	0.398*	-0.403
	(0.057)	(0.223)	(0.250)
Cost	−0.226***	-	-
	(0.062)		
Progressive*Education	-0.036	-	-
	(0.041)		
Earmarking for environmental policies*Education	0.036	-	-
	(0.041)		
Progressive*Employment	-0.020	-	-
	(0.017)		
Earmarking for environmental policies*Employment	0.033*	-	-
	(0.018)		
Progressive*EAI	0.061***	-	-
	(0.020)		
Earmarking for environmental policies*EAI	0.146***	-	-
	(0.042)		
Log-likelihood	-9277.42		
Pseudo R^2	0.109		
Number of respondents	1252		
Number of observations	15024		

Notes: ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses. The base level of each attribute is 'regressive', 'no', 'general fund revenue', respectively. Education is a binary variable that takes the value of one if the respondent has at least a high school diploma and zero otherwise. Employment is a binary variable that take the value of one if the respondent is employed and zero otherwise, and EAI is the environmental awareness index.

Table 6

Criteria for determining the optimal number of segments

Number of classes	Log-likelihood (LL)	Pseudo R^2	AIC	BIC
1	-19293.27	0.073	38598.54	19322.12
2	-9263.52	0.109	18559.04	9340.46
3	-9248.78	0.110	18549.56	9373.81
4	-9230.61	0.111	18533.21	9403.72
5	-9215.47	0.112	18522.94	9436.67

Notes: AIC (Akaike Information Criterion) is -2(LL-k) where k is the number of parameters to be estimated in the model; Pseudo R^2 is 1-(LL)/LL(0); BIC (Bayesian Information Criterion) is $-LL + (k/2) * ln(N)$ where N is the number of observations.

Table 7

LC model estimates for carbon tax attributes

	Utility parameters		Marginal WTP	
	Segment 1	Segment 2	Segment 1	Segment 2
Neutral	−0.001	0.065***	−0.011	0.283***
	(0.032)	(0.013)	(0.279)	(0.059)
Progressive	0.405***	0.090***	3.525***	0.387***
	(0.034)	(0.013)	(0.496)	(0.061)
Raising awareness towards climate change	0.279***	0.088***	2.427***	0.380***
	(0.021)	(0.008)	(0.346)	(0.038)
Earmarking for income redistribution	−0.093**	0.104***	−0.815***	0.448***
	(0.028)	(0.14)	(0.260)	(0.061)
Earmarking for environmental policies	1.292***	0.052***	11.224***	0.227***
	(0.048)	(0.016)	(1.364)	(0.070)
Cost	−0.115***	−0.232***	-	-
	(0.014)	(0.006)		
	Segment membership function			
Constant	−3.689***			
	(0.352)			
Education	0.414***			
	(0.125)			
Employment	0.322***			
	(0.125)			
EAI	0.668***			
	(0.072)			
Log-likelihood	-9263.52			
Pseudo R^2	0.109			
Number of respondents	1252			
Number of observations	15024			

Notes: ***, ** and * indicate that the estimated coefficients are statistically significant at the 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses. The base level of each attribute is ‘regressive’, ‘no’, ‘general fund revenue’, respectively. Education is a binary variable that takes the value of one if the respondent has at least a high school diploma and zero otherwise. Employment is a binary variable that take the value of one if the respondent is employed and zero otherwise, and EAI is the environmental awareness index.

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