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Carbon tax incidence on household demand: Effects on welfare, income inequality and poverty incidence in Thailand

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ABSTRACT

Studying the impact of a carbon tax on household demand can be relevant in terms of securing public acceptance of a carbon tax and clarifying the implications for policy design. This paper aims to fill a gap in the academic literature by simulating carbon tax scenarios and estimating distributional effects of the tax on household welfare, income inequality, and poverty rates based on household consumption in Thailand. The study employs a microsimulation model incorporating the economy-wide effects of the tax on prices and consumers' behavioral responses to changes in prices. The results indicate that a carbon tax is progressive in Thailand under revenue-recycling scenarios by expanding social transfer programs. When carbon tax revenues are recycled through pensions for elderly people, the carbon tax could reduce the poverty rate and improve the welfare of households in the lowest quintile. The results imply that the distributional impacts of environmental taxes could result in favorable outcomes for income inequality and poverty reduction in developing countries.

1. Introduction

The importance of mitigation policies in resolving energy and climate problem has become obvious around the world over the past few decades. Thailand submitted its intended nationally determined contributions (INDCs) proposal in October 2015, outlining a plan to reduce its greenhouse gas emissions by 2030. The choice of mitigation mechanisms to achieve climate mitigation targets will impose policy challenges in terms of the policies' effectiveness and sustainability.

The use of market-based mechanisms, such as carbon pricing, has long been a strategy to reduce carbon emissions in developed countries. This approach has been receiving more attention in developing countries in recent years. Following the Paris Agreement in 2015, experts from the International Monetary Fund recommended the use of carbon taxes to fulfill INDC plans in developing economies (Farid et al., 2016). Singapore proposed a plan to impose a carbon tax in 2019, which will be the first national carbon tax introduced in Southeast Asia. Nurdianto and Resosudarmo (2016) recommended implementing a carbon tax in Association of Southeast Asian Nations (ASEAN) countries as an effective mechanism to reduce carbon emissions and a corrective measure for energy price distortions (e.g., heavy energy subsidies in some ASEAN countries). Energy subsidies can worsen the wealth gap, and poorer people tend to receive fewer subsidies than richer people, for example, in China (Chen, 2017). A carbon tax can be an instrument for policy reform to narrow the wealth gap. Compared to cap-and-trade, which is another carbon pricing mechanism, a carbon tax is easier to implement because it can rely on existing administrative energy tax structures and does not require the establishment of an emission trading market under cap-and-trade, which is nascent in most developing countries.

The attractiveness of a carbon tax policy has encouraged the consideration of an introduction of the carbon tax in Thailand as a mechanism to achieve environmental targets. According to the statistics from EPPO (2018), Thailand's energy sector contributed to 254.4 million tons of CO_2 emissions in 2015, mainly comprising of emissions from power generation (38%), industry (30%) and transport (24%) sectors. A carbon tax on fossil fuels could provide incentives for shifting towards more renewable and sustainable clean energy in the long-term (Kossoy et al., 2015).

However, concern about possible adverse distributional impact on income inequality and poverty could provoke public resistance

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and hamper the acceptability of introducing carbon taxes (Baranzini et al., 2017). Consumption patterns largely determine differences in such distributional outcomes in lower- and mid-income countries (Dorband et al., 2019). Thus, the distributional impact of the policy on household welfare (i.e., measured by changes in household consumption in response to price changes induced by a carbon tax), income inequality and poverty reduction may represent an important barrier to introducing a carbon tax in developing countries, including Thailand. The effects of a carbon tax on income inequality and poverty reduction can be especially relevant in terms of public acceptance of the policy in developing countries and impact policy design.

In the context of distributional impact studies, the incidence of a carbon tax is regressive when its adverse welfare effects on low-income households are proportionally larger than on high-income households and vice versa. The regressive aspect of the tax worsens income inequality and, most likely, poverty rates. Existing studies imply that a carbon tax is regressive in most developed countries as summarized in Appendix A. However, the tax does not need to be regressive in developing countries. There is little research evidence of the distributional effects of a carbon tax in developing countries compared to the vast amount of evidence in developed countries. For example, a carbon tax was found to be progressive in Indonesia (Yusuf and Resosudarmo, 2015). The progressive effect of a carbon tax was also found in Mexico when the carbon tax revenue was recycled through a food subsidy (Gonzalez, 2012). Similarly, the redistribution of simulated tax revenues through a social welfare program could result in progressive outcomes and reduce poverty in Mexico (Renner et al., 2018). However, mixed results have been found in China (Brenner et al., 2007; Jiang and Shao, 2014; Chen et al., 2015).

With limited evidence in general for developing countries and no empirical analysis of distributional effects of a carbon tax in Thailand, a general finding of regressive carbon taxes in developed countries may invoke adverse public concerns about the policy despite its potential for addressing energy and environmental challenges. Several existing studies of a carbon tax in Thailand examine the effects of a carbon tax on economy and carbon reductions using a computable general equilibrium model (Wachirarangsrikul et al., 2013; Puttanapong et al., 2015; Wattanakuljarus, 2018). Some studies have aimed to analyze the appropriate level of a carbon tax to achieve carbon dioxide (CO_2) reduction targets (Chunark et al., 2014) or make renewable energy, such as biomass, competitive with fossil fuels in power generation (Santisirisomboon et al., 2001). Specific in-depth analyses of carbon tax distributional effects on household welfare based on consumption are relatively scarce in Thailand. A recent study by Saelim (2019) estimates the first-round effect of a carbon tax on household consumption (excluding behavioral responses) and examines the association between its welfare effects and socio-economic factors of households in Thailand. However, there has not been any attempt to examine policy implications of the distributional effects of a carbon tax, incorporating households' behavioral response to price changes, on household welfare, income inequality and poverty incidence in Thailand.

Thus, this paper aims to fill a gap in the literature by simulating carbon tax scenarios (ex-anti analysis) and estimating distributional effects on household welfare, income inequality, and poverty incidence based on household consumption in Thailand. The study employs a microsimulation model incorporating the economy-wide effects of the tax on prices (through an input-output model) and households' behavioral responses to price changes induced by the tax (through demand system estimations). This study also utilizes disaggregated data from Thai household surveys, which is absent in most existing carbon tax studies that include Thailand's data.

The novelty of this study is to inform carbon tax policy design in addressing the following three aspects of policy questions:

- *Effectiveness*: Does a carbon tax effectively reduce energy consumption in the residential sector? Which household groups are more responsive to price changes induced by a carbon tax?
- *Equity*: Does a carbon tax cause an unequal impact on household welfare? Which household groups are more likely to suffer larger welfare losses?
- *Social*: Does a carbon tax worsen social development objectives, such as income inequality and poverty rates? Which revenue-recycling options should be considered to minimize adverse impacts on social objectives?

It should be noted that the scope of this study does not include estimating the optimal level of the carbon tax but focuses on the distributional effects on households. The study applies a partial equilibrium framework, which analyzes the effects of the tax only on household consumption, with the assumption of no effects on household income and no reallocation of input in the production factors. The analysis, however, partly incorporates the economy-wide impact on price changes in all economic sectors captured by an input-output model. The study also excludes potential welfare benefits from the reallocation of input towards cleaner energy, assuming no feedback effect of a cleaner environment in consumer utility when assessing the welfare effects on households.

Although the distributional impact on household demand is only a part of the carbon tax story, it is very important for policy analysis, both in terms of securing public acceptance and policy design, such as revenue-recycling options to reduce adverse effects on low-income households. In addition to its contribution to national policy, this study attempts to contribute to the existing literature on the distributional effects of carbon taxation in developing countries, serving academic interests in terms of research on carbon abatement policies.

2. Literature review on distributional effects of carbon taxes

Distributional effects of a carbon tax in developed countries have been widely researched, and the existing literature on these effects are summarized in Appendix A. However, existing studies of the distributional incidence of the carbon tax in developing countries are limited but growing. According to a recent comprehensive review of studies on distributional effects of a carbon tax (Wang et al., 2016), most studies show that the carbon tax is regressive in developed countries, while the studies focusing on developing countries have recently evolved and are still too inconsistent to draw a general conclusion.

The regressivity of a carbon tax in most developed countries, such as in the United Kingdom (Feng et al., 2010), the Netherlands (Kerkhof et al., 2008) and Denmark (Wier et al., 2005), indicates that low-income households' expenditure patterns in these countries tend to be more carbon-intensive in energy consumption for housing, food, and public transport than those of high-income households. The primary reason for the regressive carbon tax also lies in higher carbon tax burdens attributable to domestic energy consumption (e.g., heating, cooking, and lighting) for lower-income households in developed countries. However, a regressive carbon tax could be very small and easily compensated by revenue recycling as is the case in New Zealand (Creedy and Sleeman, 2006). Additionally, a carbon tax might be weakly progressive in some developed countries, for example, in Italy. The progressive result in Italy is driven by the greater consumption of transport fuels by high-income households, who are more likely to own a car than poorer households (Tiezzi, 2005).

With limited evidence of the distributional effects of a carbon tax in developing countries, the regressive incidence of the carbon tax in most developed countries should not be generalized to developing countries, primarily due to different household consumption patterns. Carbon tax burdens on low-income households tend to be higher in developed countries, which is attributable to their higher consumption share of fuels for home heating compared to wealthier households (Brännlund and Nordström, 2004; Mathur and Morris, 2014; Symons et al., 1994; Wier et al., 2005). This energy consumption pattern is a rare case for developing countries, which are more likely to be located in tropical and subtropical climates. Furthermore, the incidence of carbon taxes could be different between developed and developing countries due to institutional factors (Shah and Larsen, 1992). Studies suggest that household consumption patterns in developing countries are significantly different from those in developed countries; for example, high-income households tend to spend a larger share of their income on energy because they are more likely to own and use motor vehicles (Wang et al., 2016). Thus, despite the lack of quantitative studies, distributional concerns should not necessarily prevent ample opportunities for developing countries to introduce a carbon tax to mitigate carbon emissions.

For developing countries, a few existing studies suggest that a carbon tax could have progressive effects. For example, the overall incidence of a carbon tax is progressive in China, driven by a larger share of expenditures on energy and industrial goods (i.e., the most carbon-intensive sectors in China) for urban households, which have higher income levels on average (Brenner et al., 2007). A carbon tax is found to be progressive in Indonesia as poorer households tend to use less energy, especially those living in rural areas (Yusuf and Resosudarmo, 2015). Similarly, progressive outcomes of a carbon tax are found in Mexico with revenue-recycling scenarios (Gonzalez, 2012; Renner et al., 2018).

Carbon tax incidence could be altered several ways depending on the methodology applied in the analysis, including different model approaches and various underlying assumptions. The first difference is carbon tax assumptions, or the levels of hypothetical carbon tax rates, applied in the simulation models. Also, some studies analyze the effects of a carbon tax both directly on the consumption of fossil fuels (direct effects) and indirectly on the consumption of other goods and services which use fossil fuels in their production process (indirect effects). However, some studies exclude a carbon tax's indirect effects due to limitations in data availability, and excluding these effects in the distribution analysis of a carbon tax may lead to a distorted picture of the tax incidence as indirect effects are often much larger than direct effects in some countries (Symons et al., 1994; Brenner et al., 2007; Jiang and Shao, 2014; Mathur and Morris, 2014). For example, in the Shanghai region of China, the overall incidence of a carbon tax is regressive, driven by larger indirect effects of the tax on low-income groups (Jiang and Shao, 2014).

Some studies of distributional effects of carbon taxes incorporate behavioral responses (e.g., the elasticity of demand to price changes) into the analysis (Symons et al., 1994; Cornwell and Creedy, 1996; Labandeira and Labeaga, 1999; Brännlund and Nordström, 2004; Renner et al., 2018). Other studies analyze the tax incidence based on consumer expenditure surveys, assuming no behavioral responses due to the limitations of available price data. How households respond to price changes induced by the tax could reduce tax burdens for households with higher elasticity demand to price changes.

Moreover, the carbon tax incidence could vary depending on carbon tax scenarios under different revenue-recycling schemes. The degree of regressive or progressive incidence depends on how the revenues are recycled in the simulation exercises. For example, some revenue-recycling schemes could worsen the regressive outcomes of the tax, as found in the United States. In this case, the use of carbon tax revenues to reduce corporate or personal income tax exacerbates the regressive incidence as high-income households are more likely to receive the benefits of an income tax reduction (Mathur and Morris, 2014). The regressive incidence of the carbon tax could also turn to be progressive when revenues are recycled through the reduction of value-added tax and benefit payments, as found in the United Kingdom (Symons et al., 1994). Similarly, the regressive incidence could be remedied in Ireland with the redistribution of carbon tax revenues by increasing tax credits and reducing income tax (Callan et al., 2009). A revenue-recycling scheme may also have more favorable distributional outcomes over other schemes. For example, in Indonesia, a revenue-recycling policy through a uniform reduction of the sales tax led to a more favorable distribution impact and poverty reduction than through lump-sum transfers (Yusuf and Resosudarmo, 2015). Thus, the choice between alternative revenue-recycling policies can significantly influence the distribution effects of a carbon tax.

Most studies on the distributional effects of a carbon tax are based on a partial equilibrium framework with the assumption of no effects on household income. Due to the availability of data and the model's complexity, the disaggregated data from household surveys are unlikely to be utilized under the general equilibrium framework. Only a few studies (Gonzalez, 2012; Yusuf and Resosudarmo, 2015) incorporate distributional effects under the general equilibrium framework. However, an analysis under a partial equilibrium framework allows deeper analysis of the effects on each household group and the estimation of household demand.

3. Methodology

Microsimulation models have been mostly used in recent studies to estimate the distributional effects of energy and climate policies on household welfare under partial equilibrium frameworks. They have incorporated households' behavioral responses to changes in energy prices into the analysis (Tiezzi and Verde, 2016; Rosas-Flores et al., 2017; Schulte and Heindl, 2017; Moshiri, 2015; Nikodinoska and Schröder, 2016). The methodology for this study also employs a microsimulation model incorporating a demand system estimation to evaluate the carbon tax incidence based on household demand. The following sub-sections describe the assumptions and the model's approach to calculating the effects of a carbon tax on households. Key variables are summarized in Table 1.

3.1. Carbon tax assumptions

The choice of the optimal carbon tax rate for each country is

Table 1
Summary of notations for key variables.

Symbol	Definition
p	Vector of producer prices
A	Vector of share of input i in the production output j
v	Vector share of value added to the production output
CV	Compensating variation, used as a measure of welfare
m	Consumption expenditure
k	Number of consumption category
w_i	Share of good i in consumption expenditure
p_i	Price index of good i
p_j	Price index of good j
ε_{ij}	Own- and cross- price elasticities
ε_m	Expenditure elasticity

arbitrary depending on various underlying assumptions, such as emission targets, efficiency, and equity issues, and social and political perspectives, so determining the optimal tax level in Thailand requires further study. Depending on how the government makes policy strategy, the methodology to solve multiple criteria decision-making problems could be used to determine the optimal carbon tax rate. For example, Jin et al. (2018) proposed the use of a centralized data envelopment analysis to solve conflicting objectives of the government (e.g., a carbon tax may lead to lower carbon emissions but higher government expenditures) in determining the optimal carbon tax policy.

Based on the theoretical economic concept, the optimal tax rate should be set at the marginal social cost of carbon (SCC), which internalizes the cost of a negative externality, a so-called Pigouvian tax. Considering the absence of an existing carbon tax policy framework in Thailand, this study assumes a hypothetical carbon tax rate at the estimated SCC level of US$ 37 (or Baht 1197) per ton of CO_2 (IAWG, 2015). It should be noted that this rate is high compared to the actual carbon tax rates practically implemented in most countries, which are much lower than the SCC level (e.g., less than US$10) for political, social, or practical reasons (Kossoy et al., 2015). The carbon tax rate at SCC level assumed in this study illustrates the upper bounds of the carbon tax effects on household demand, representing the potential worst-case scenario of its negative effects on income inequality and poverty reduction, which are the public's concerns.

As a starting point, the hypothetical carbon tax is assumed to be levied directly on emissions from fossil fuels (i.e., coal, natural gas, and oil) in two energy production sectors, petroleum refineries, and electricity generation. The carbon tax amount is calculated based on fossil fuel (in tons of CO_2) emission data and the assumed carbon tax rate per ton of CO_2. This amount increases producers' prices in these two energy production sectors and other industrial sectors that use energy goods in their production process. Increases in producers' prices in each industrial sector can be calculated using the price input-output model described in Section 3.2.

Given the assumption that fuel price increases are fully passed on to consumers, the carbon tax would directly raise the consumption prices of energy (i.e., electricity and transport fuels) and indirectly increase the prices of non-energy goods and services that use energy in the production process. The carbon tax is simulated to have taken effect in the year 2013 for this study, based on the availability of the latest Thai Household Socio-Economic Survey data. The share of energy consumption in household expenditures was stable at 10–11% between 2007 and 2016 (NSO, 2018).

3.2. *Effect on prices (input-output model)*

The price input-output model is employed in this study to capture the economy-wide effect of the carbon tax on the prices of all goods and services produced in the economy. This price input-output model has been adopted in a number of studies to calculate price effects from energy and climate change mitigation policies (Arndt et al., 2011; Hassett et al., 2009; Ogarenko and Hubacek, 2013). The changes in producer's prices derived from the price input-output model can be written in the form of

$$\Delta p = \left(1 - A'\right)^{-1} \Delta v \tag{1}$$

where the changes in producer prices (Δp) equal the multiplication of input coefficient matrix, $\left(1 - A'\right)^{-1}$, the well-known Leontief inverse matrix, and the change in vector share of total value added to the production output, Δv. The carbon tax affects the producer prices in all industrial sectors through the increase in total value added resulting from the imposition of the carbon tax on electricity and petroleum products sectors. The changes in producer prices of industrial sectors represent the changes in prices of consumption categories used to estimate the welfare effects.

3.3. *Effects on household welfare*

In this study, compensating variation (CV) is used to evaluate the welfare impact of price changes. CV is the amount of money that households need to maintain the pre-tax level of utility given a new set of prices induced by the policy defined in the form of a money metric function of $CV = e(p^1u^0) - e(p^0u^0)$ where $e(p,u)$ is the expenditure function of price vector p and utility u. The superscript 0 represents the pre-tax level, and 1 represents the post-tax level. Using Shephard's lemma and a second-order Taylor's approximation of money metric function as well as dividing both sides by total consumption, the relative welfare effect on each household can be calculated in the form of

$$CV/m = \sum_{i=1}^{k} w_i\left(\frac{\Delta p_i}{p_i}\right) + \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k} w_i\varepsilon_{ij}\left(\frac{\Delta p_i}{p_i}\right)\left(\frac{\Delta p_j}{p_j}\right) \tag{2}$$

where the relative welfare effects as the percentage of consumption expenditure (m), CV/m, can be described as the function of three variables: the budget share of good i (w_i), changes in prices (Δp_i), and compensated own- and cross-price elasticities (ε_{ij}). Consumption expenditure can be divided into four types of consumption goods ($k = 4$) in this study: electricity, transport fuels, food, and non-alcohol beverages and other non-durable expenditures. In this study, households are ranked into five quintiles based on equivalized consumption, which represents individual welfare. The equivalized consumption is computed based on a two-parameter functional form of an adult equivalence scale, described in the work of Saelim (2019).

3.4. *Compensated price elasticities estimated from the demand estimation model*

The Quadratic Almost Ideal Demand System (QUAIDS) model is used to obtain compensated price elasticities which represent the behavioral response of households to changes in energy prices. The QUAIDS model allows a welfare analysis to be consistent with consumer demand theory and flexible with a rank-three demand system to incorporate the nonlinearity patterns in the observed consumption from the survey data.

Banks et al. (1997) introduced the QUAIDS model by adding a quadratic term to the budget share equations of the original Almost Ideal Demand System (Deaton and Muellbauer, 1980) while keeping theoretical properties relevant. Under the QUAIDS model, the budget shares of good i can be derived in the form of

$$w_i = \alpha_i + \sum_{j=1}^{k}\gamma_{ij} ln p_j + \beta_i ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_i}{b(p)}\left\{ln\left[\frac{m}{a(p)}\right]\right\}^2 \tag{3}$$

where ln $a(p)$ or price index has a translog form of

$$ln a(p) = \alpha_0 + \sum_{i=1}^{k}\alpha_i ln p_i + \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}\gamma_{ij} ln\, p_i ln\, p_j \tag{4}$$

$b(p)$, the Cobb-Douglas price aggregator and $\lambda(p)$ has the form of

$$b(p) = \prod_{i=1}^{k} p_i^{\beta_i} \tag{5}$$

$$\lambda(p) = \sum_{i=1}^{k} \lambda_i lnp_i \tag{6}$$

To be consistent with economic theory, theoretical restrictions (i.e., adding, homogeneity and symmetry restrictions: $\sum_{i=1}^{k} \alpha_i = 1$, $\sum_{i=1}^{k} \beta_i = 0$, $\sum_{j=1}^{k} \gamma_{ij} = 0$ $\sum_{i=1}^{k} \lambda_i = 0$, *and* $\gamma_{ij} = \gamma_{ji}$) are imposed when estimating budget share equations, in which a two-stage budgeting process is assumed where households decide to allocate between durable and non-durable consumption in the first stage and make decisions to allocate among the groups of non-durable consumption in the second stage. The demand system in the second stage consists of four budget share equations that represent energy (i.e., electricity and transport fuels) and non-energy (i.e., food and non-alcohol beverages and other non-durable goods and services) demand in Thailand. Transport fuels based on Thai household survey data include diesel, benzene95, benzene91, gasohol95 and gasohol91.

Econometric specification of the QUAIDS model are provided in Appendix B. Parameter estimates obtained from the QUAIDS model are then used to compute expenditure and price elasticities in the following form (Lecocq and Robin, 2015):

- *The expenditure elasticities:*

$$\varepsilon_m = \mu_m / w_i + 1 \tag{7}$$

where. $\mu_m = \frac{\partial w_i}{\partial lnm} = \beta_i + \frac{2\lambda_i}{b(p)} \left(ln\left[\frac{m}{a(p)}\right] \right)$

- *The uncompensated price elasticities (under Marshallian demand):*

$$\varepsilon_{ij}^{u} = \mu_{ij} / w_i - \delta_{ij} \tag{8}$$

where. $\mu_{ij} = \frac{\partial w_i}{\partial lnp_j} = \gamma_{ij} - \mu_m \left(\alpha_i + \sum_k \gamma_{jk} lnp_{k)} - \frac{\lambda_i \beta_j}{b(p)} \left\{ ln\left[\frac{m}{a(p)}\right] \right\}^2 \right.$ and δ_{ij} is the Kronecker delta.

- *The compensated price elasticities (under Hicksian demand):*

$$\varepsilon_{ij}^{c} = \varepsilon_{ij}^{u} + w_j \, \varepsilon_m \tag{9}$$

which is derived from the Slutsky equation.

3.5. Effects on income inequality and poverty incidence

The main criticisms in terms of the distributional issues of a carbon tax policy are the carbon tax's potential adverse effects on social objectives, such as income inequality and poverty rates. In this study, the Gini index is used as an inequality indicator as typically applied in empirical work in the following form:

$$Gini = \frac{2cov(Y,F)}{\bar{y}} \tag{10}$$

where $cov(Y,F)$ is the covariance between household income and its rank (F) in the distribution and $\bar{y}$ is the average level of income. The values of the Gini index range between zero and one: zero values indicate perfect equality in income distribution, and values approaching one indicate higher levels of inequality.

A carbon tax's effects on poverty are measured by changes in poverty rates, comparing poverty rates under the status quo and under carbon tax scenarios. The poverty rate represents the percentage of poor households in the total population. Poor households refer to those having consumption expenditures below the national poverty lines for each region and municipality. Changes in poverty rates represent the difference between the estimated poverty rate (post-tax) and the initial level (status quo), both expressed in percentages. Positive numbers indicate increases in poverty rates and negative numbers mean reductions in poverty rates under given carbon tax scenarios compared to the status quo.

4. Data

This study utilizes data from three main sources, which are Thai household survey data, consumer price index data and input-output data.

(1) *Household income and expenditure survey:* The National Statistical Office (NSO) conducts a national Thai Household Socio-economic Survey (SES) annually to survey consumption and in odd years to survey income. The SES follows a stratified two-stage sampling method. The samples constitute 77 strata based on provinces, and each stratum (except Bangkok metropolitan) is divided into urban and rural areas based on the type of local administration (i.e., municipal and non-municipal). In the first stage, or for the primary sampling unit, the enumeration area is assigned separately and independently. Then, the next stage is to select private sample households systematically: 15 urban households and 10 rural households. The stratification and sampling weights are assigned in the survey setting to represent the mean estimates for the whole population in this study.

(2) *Consumer price indices:* Monthly consumer price indices are published by the Bureau of Trade and Economic Indices, Ministry of Commerce. The indices are calculated based on the modified Laspeyres' formula in the form of

$$Price\ Indices\ (PI) = \frac{\sum_i^k w_{i0} \frac{p_{it}}{p_{i0}}}{\sum_i^k w_{i0}} *100 \tag{11}$$

where w_{i0} is a weight in the reference period (i.e., year 2011). This formula is also applied to calculate a price index for aggregation of other non-durable consumption. p_{it} is the price index of good i in period t. p_{it} is the price index of good i in the reference period.

(3) *Input-output data:* The National Economic and Social Development Board (NESDB), the official focal point for economic data in Thailand, provides input-output data every five years. The latest data available is for the year 2010. The input-output data includes transactions between 180 industry sectors, which are regrouped into 37 sectors in this study for distributional analysis. The 37 industry sectors from the input-output table are then categorized into 12 consumption groups to match with household consumption data from the national survey.

For data used to establish demand estimation and obtain expenditure and price elasticities, cross-sectional SES data for the years 2009, 2011, and 2013 are pooled as a dataset for the estimation of the QUAIDS model. The pooled dataset consists of 128,655 observations, which allows the distribution of observations across time (i.e., the year and month of the interview) and regions. A number of observations have been dropped to ensure correspondence between the expenditure in the survey and price index data and to correct for outliers. The final dataset for demand estimation is reduced to 114,470 observations to better represent the majority of the population and correspond to the available price indices.

For the simulation of distributional effects, the SES data for the year 2013 is used to represent the whole population. The sample size is 42,738 observations, corresponding to a total of 20.2 million households in Thailand, using the assigned sampling weight to obtain the entire population data. As the Thai survey data over-samples the urban population, omitting survey design specifications can lead to biased estimators and incorrect standard errors (O'Donnell et al., 2008 and Ala-Mantila et al., 2014), so the survey setting (e.g., sampling weights and stratification) is used in this study to obtain appropriate conditional means of the population (Deaton, 1997).

Regarding socio-demographic characteristics of the Thai population in 2013, Thai households are more concentrated in rural areas, with the urbanization rate of only 36%. However, the urbanization increases at the higher end of the income distribution, with about 60% of households in the top quintile living in urban areas. The majority of low-income households in Thailand lives in the Northeast and the North and mainly earn income from agricultural activities and non-economic activities such as elderly pension. High-income households are more concentrated in Bangkok and the Central regions and mainly earn income from high-skill work and non-farm businesses.

5. Results

5.1. Response of household demand to changes in energy prices

Expenditure and price elasticities across household groups determine the vulnerability of households in reducing their consumption when energy prices increase as a result of a carbon tax. They measure the effectiveness of a pricing policy, such as a carbon tax, in reducing household energy consumption through increases in energy prices.

Table 2 presents the computed expenditure and price elasticities using parameters estimated from the QUAIDS model (see Appendix B). Overall, the expenditure elasticities indicate that electricity is a necessity, whereas transport fuels are unit elastic. For example, a 1% increase in income (using non-durable consumption expenditure as a proxy) raises the demand for electricity by 0.634% and transport fuels by 1.001%, on average. The aggregate food and non-alcohol beverage group comprises necessity goods as expected, while the other non-durable consumption category (Others) consists of luxury goods (i.e., income elasticity is equal to 1.267).

Considering the sample means of subgroups based on income distribution, transport fuels are a luxury for low-income groups (1.311) but a necessity for high-income groups (0.735). Comparing income elasticity estimates with existing studies, Havranek and Kokes (2015) reported a mean income elasticity of gasoline demand of 0.66 in the long-term from meta-analysis results. Fouquet (2012) suggests that transport demand elasticities in developing economies, which are often larger than developed economies, may exhibit a declining trend as the economies enlarge, a conclusion drawn from the United Kingdom's experience (1850–2010).

With regards to uncompensated elasticities, own-price elasticities imply that both electricity and transport fuels are inelastic to price changes; however, the demand for transport fuel is more sensitive to price changes than electricity. Low-income households tend to be less sensitive to energy price changes than high-income groups. The compensated own-price elasticities indicate similar patterns but at lower absolute terms as only the substitution effect is included, while uncompensated price elasticities incorporate both substitution and income effects. Comparing price elasticity estimates with empirical studies, Labandeira et al. (2017) reported the estimated average price elasticities of energy demand from their meta-analysis results are −0.608 in the long-term. They also concluded that energy products are price inelastic.

5.2. Effects of a carbon tax on welfare across household groups

The distributional effects of a carbon tax on household welfare depend on the magnitude of price changes, the importance of energy in a households' budget share, and behavioral responses to price changes. The carbon tax directly raises the price of electricity and petroleum products by 17.1% and 9.2%, respectively, and indirectly raises the price of other goods and services in the range of 0.3–3.8% as shown in Table 3. Overall, Thai households spend approximately 11% on energy consumption on average, which can be sub-categorized as 7.9% spent on petroleum products and 3.5% on electricity, while food and beverage expenditures account for the largest share, about 45% of total consumption.

Table 4 presents total aggregate welfare losses induced by a carbon tax across households in different quintiles based on equivalized consumption. The average monthly welfare loss for all households is estimated at 442 baht per household. Monthly welfare loss for the whole population totals 8.92 billion baht, 41% of which is incurred by households in the top quintile compared to only 8% incurred by households in the bottom quintile.

Relative welfare losses across households at different quintiles are presented in Table 5. Direct effects of a carbon tax on electricity consumption are found to be regressive, while welfare losses from transport fuel consumption indicate progressive patterns. Comparing the relative welfare effects across the income distribution, the mid-income groups seem to suffer the largest percentage of welfare losses, influenced by higher direct effects on energy consumption. Meanwhile, indirect welfare effects from non-energy consumption show regressive patterns.

As discussed in the literature review, the use of carbon tax revenues to compensate households through revenue-recycling schemes could play a significant role in altering the distributional results of a carbon tax. According to the global experience, Carl and Fedor (2016) report that carbon tax revenues are often used as revenue-recycling schemes (e.g., to compensate businesses or households through tax cuts and rebates granted to households) compared to other schemes, such as green spending and general funds.

Based on information available in the survey data and revenue-recycling options applied in the carbon tax literature, four revenue-recycling options are considered when simulating carbon tax scenarios: (1) equal lump-sum transfers, (2) increase transfers through existing elderly pensions, (3) increase transfers through the existing food support program, and (4) reduce income taxes. A proportion of carbon tax revenues has been postulated as rebates to households under each carbon tax scenario as described in Table 6. The compensation package used in each scenario is calculated based on the same total amount of the whole cost, around 3.57 billion baht in each scenario, to compare the impact of each revenue-recycling option. This compensation amount is calculated at 40% of carbon tax revenues from households, measured by total compensation variation, the assumed proportion based on the evidence compiled in the work of Carl and Fedor (2016).

Fig. 1 compares welfare losses from a carbon tax in each scenario. Without a revenue-recycling option, households at the middle-income distribution level suffer the largest percentage of welfare losses. The reduction in welfare losses under each revenue-recycling option compared to proceeding without a compensation scenario varies across quintiles. Households in the lowest quintile receive a welfare gain of 2.8% under the Pension scenario. Meanwhile, they suffer the largest welfare loss under the Tax cut

Table 2
Expenditure and price elasticities by income group.

	Predicted budget share	Elasticities		
		Expenditure	Price (ε_{ij}^{u})	Price (ε_{ij}^{c})
Panel A: All households				
Electricity	0.036***	0.634***	−0.526***	−0.503***
		(0.0070)	(0.0130)	(0.0130)
Transport fuels	0.078***	1.001***	−0.602***	−0.524***
		(0.0090)	(0.0210)	(0.0210)
Food and beverages	0.466***	0.787***	−0.875***	−0.508***
		(0.0030)	(0.0040)	(0.0040)
Others	0.421***	1.267***	−1.066***	−0.533***
		(0.0030)	(0.0060)	(0.0060)
Panel B: Low-income group				
Electricity	0.035***	0.656***	−0.521***	−0.498***
		(0.0070)	(0.0130)	(0.0130)
Transport fuels	0.059***	1.311***	−0.514***	−0.436***
		(0.0120)	(0.0280)	(0.0280)
Food and beverages	0.531***	0.827***	−0.894***	−0.455***
		(0.0030)	(0.0040)	(0.0040)
Others	0.375***	1.229***	−1.052***	−0.591***
		(0.0040)	(0.0070)	(0.0070)
Panel C: Middle-income group				
Electricity	0.035***	0.623***	−0.522***	−0.500***
		(0.0080)	(0.0130)	(0.0130)
Transport fuels	0.078***	0.936***	−0.596***	−0.523***
		(0.0090)	(0.0210)	(0.0210)
Food and beverages	0.452***	0.776***	−0.869***	−0.518***
		(0.0030)	(0.0040)	(0.0040)
Others	0.434***	1.276***	−1.070***	−0.516***
		(0.0030)	(0.0060)	(0.0060)
Panel D: High-income group				
Electricity	0.036***	0.603***	−0.531***	−0.509***
		(0.0100)	(0.0130)	(0.0130)
Transport fuels	0.097***	0.735***	−0.647***	−0.576***
		(0.0100)	(0.0170)	(0.0170)
Food and beverages	0.361***	0.697***	−0.837***	−0.586***
		(0.0060)	(0.0060)	(0.0050)
Others	0.506***	1.296***	−1.087***	−0.432***
		(0.0030)	(0.0050)	(0.0050)

Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Note: Low-income group refers to households in the lowest two quintiles, and high-income group refers to households in the top quintile.

Table 3
Price changes and consumption budget share.

Consumption groups	Price changes	Budget share
Electricity	17.1%	3.5%
Petroleum products (oil)	9.2%	7.9%
Public transport	3.8%	1.1%
Water supplies	3.1%	1.0%
Clothes, household textile and footwear	2.6%	2.8%
Vehicle purchase	2.2%	4.8%
Housing, furniture, appliance and equipment	2.0%	15.8%
Other non-durable goods and services	1.8%	13.0%
Vehicle repair and maintenance	1.6%	1.5%
Food and beverages	1.3%	44.9%
Communication	1.1%	3.3%
Charcoal and wood	0.3%	0.5%

scenario, which may be due to households in the lowest quintile rarely being required to pay taxes due to their low level of income; hence, most of them do not benefit from an income tax reduction. However, households in the top quintile receive more benefits under the Tax cut scenario compared to other scenarios.

5.3. *Effects on income inequality and poverty*

The effects of a carbon tax on income inequality and poverty incidence under the status quo (i.e., the no carbon tax case) and carbon tax scenarios, with and without revenue-recycling options, are summarized in Table 6. Using Gini coefficients as inequality measures, changes in inequality indices across carbon tax scenarios

Table 4
Monthly welfare loss, measured by CV.

Household groups	Average monthly welfare loss per household (Baht)	Total monthly welfare loss (Billion Baht)	Distribution of total monthly welfare loss
Quintile 1	178	0.72	8%
Quintile 2	267	1.08	12%
Quintile 3	366	1.48	17%
Quintile 4	494	1.99	22%
Quintile 5	906	3.65	41%
All households	*442*	*8.92*	*100%*

Note: Figures represent mean estimates taking into account the sampling weights and stratification of the survey design.

Table 5
Relative welfare losses from a carbon tax, measured by CV/m.

Equivalized consumption	Direct effects			Indirect effects		
	Electricity	Transport fuels	*Total*	FB	Others	*Total*
Quintile 1	0.66%	0.49%	*1.15%*	0.69%	0.73%	*1.42%*
Quintile 2	0.61%	0.64%	*1.25%*	0.65%	0.76%	*1.41%*
Quintile 3	0.61%	0.71%	*1.32%*	0.60%	0.80%	*1.40%*
Quintile 4	0.58%	0.73%	*1.31%*	0.53%	0.85%	*1.38%*
Quintile 5	0.56%	0.74%	*1.30%*	0.39%	0.90%	*1.29%*
All	0.61%	0.66%	*1.27%*	0.57%	0.81%	*1.38%*

Note: Figures represent mean estimates of CV as percentage of consumption expenditure, taking into account the survey design.

Table 6
Description of carbon tax scenarios based on revenue-recycling schemes.

Compensation schemes	Scenarios	Total cost* (Billion Baht)	Compensation package	Number of households receiving compensation
No compensation	Without	–	–	–
Equal transfer	Transfer	3.15–3.99	177 Baht	All households
Increase in elderly pension	Pension	3.01–4.13	398 Baht	8.97 million
Increase in food support	Food	2.90–4.23	490 Baht	7.28 million
Income tax reduction	Tax cut	3.26–3.88	0.32%**	9.52 million

* 95% confidence interval.
** Reduction of taxable income in the second income tax bracket.

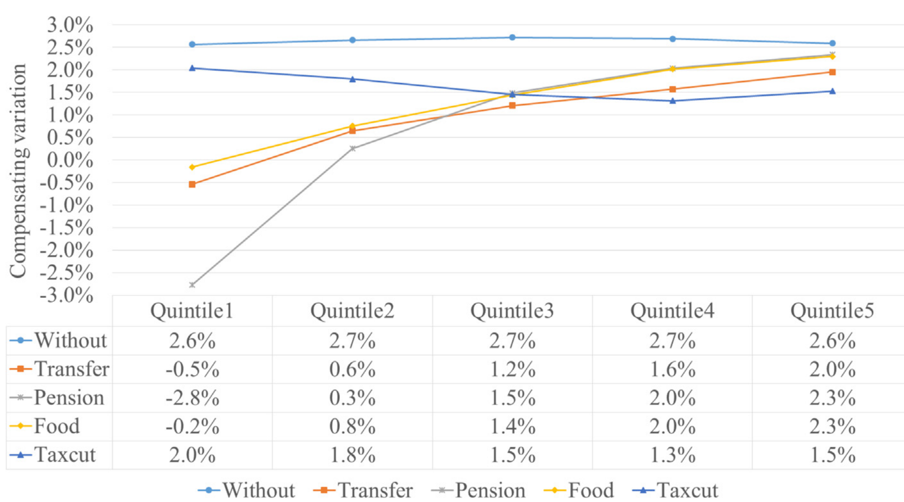


Fig. 1. Welfare losses with and without compensation policies.

with revenue-recycling options indicate that the carbon tax is progressive under three lump-sum transfer scenarios. The Pension scenario is found to be the most progressive. Without a compensation package, a carbon tax would increase the poverty rate by 1%. The effects on poverty incidence are nil under the Transfer and the Food scenarios. Interestingly, the carbon tax reduces the poverty rate by 0.3 percentage points under the Pension scenario.

6. Discussion

To inform the policy design of a carbon tax, the previous results of the study will be further discussed in an effort to address three aspects of policy questions, in terms of effectiveness, equity, and social implications.

Effectiveness: The result of inelastic price elasticity of the demand for transport fuels and electricity indicates that pricing instruments, such as a carbon tax alone, may not effectively reduce energy demand in the residential sector. Other policy instruments, such as investment in renewable energy and the improvement of public transport, are needed to allow households more choices to alter their consumption patterns. High-income households tend to be more sensitive to energy price changes than the low-income group. This could be explained by living areas and vehicle ownership in the high-income group. Fig. 2 shows that a larger proportion of households in the higher quintiles lives in urban areas and owns automobiles, pickup trucks, and vans. This indicates greater consumption of electricity and transport fuels by high-income households, and hence they are more responsive to energy price changes.

Equity: The distribution of total aggregate welfare loss as a result of the carbon tax is more concentrated in high-income households, with the proportion in the top quintile five times larger than the total aggregate welfare loss of households in the bottom quintile. Overall, the size of the carbon tax's indirect welfare effects is larger than direct effects in most quintiles, especially the bottom quintile, due to the importance of food and beverage consumption in the household budget. These results stress the importance of including indirect effects in distributional analyses of a carbon tax's impact. Omitting indirect effects may lead to a distorted picture of the tax incidence as indirect effects are often much larger than direct effects (Symons et al., 1994; Brenner et al., 2007; Jiang and Shao,

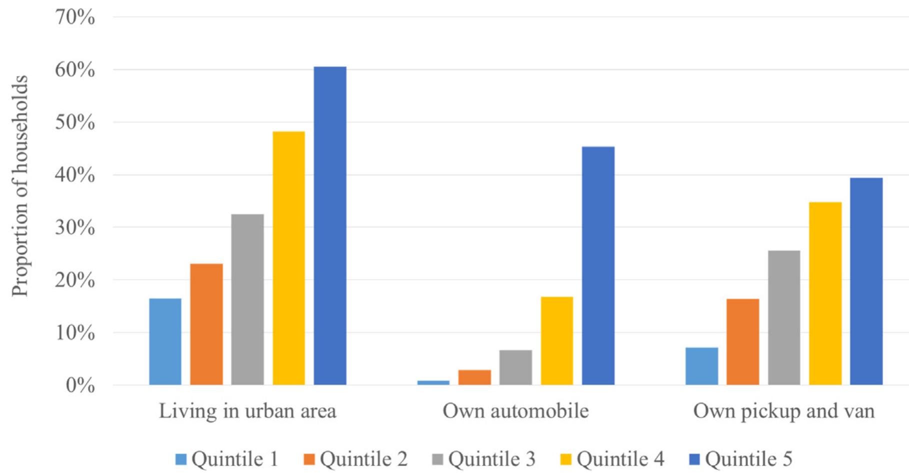
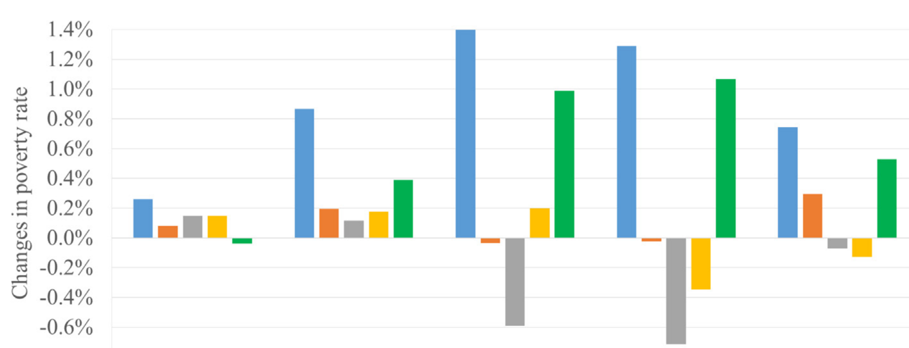


Fig. 2. Living area and vehicle ownership by each household groups.

2014). Households in higher income quintiles suffer larger relative welfare losses from the consumption of transport fuels and other non-durable consumption groups. The results support the hypothesis that the carbon tax incidence in developing countries could be progressive as poorer households in developing countries tend to have less-energy intensive consumption (Brenner et al., 2007; Gonzalez, 2012; Yusuf and Resosudarmo, 2015).

Social: A carbon tax has a small negative impact on an income inequality measure and poverty rates under the scenario of a no compensation scheme and the recycling revenue option by reducing income taxes. A carbon tax can improve income inequality and reduce poverty rates when carbon tax revenues are recycled through an increase in elderly pensions as a larger population of lower income households is entitled to receive benefits from existing elderly pensions based on the household survey data. A policy of compensating households through personal income tax reduction would at least mitigate the impact on low-income households. Considering spatial variation in effects on poverty rates by region as shown in Fig. 3, the increase in poverty rates as a result of a carbon tax is found to be the largest in the northern and the northeastern regions when no compensation package is provided. However, with a revenue-recycling scheme through elderly pensions, a carbon tax could result in poverty reduction in the northern and northeastern regions and a welfare gain for low-income households (the 1st quintile). Regional variation in poverty rates are also found in fuel subsidy reform in Nigeria, and tailored compensation schemes are recommended to account for regional variation (Rentschler, 2016).

Due to the limitations of data availability, a number of assumptions should be noted when interpreting the study's results. First, the study assumes a static input-output structure with no substitution and no substitution of factors of production (e.g., a fixed proportion of the input and, hence, labor demand and wages). Second, the study incorporates a cost-push assumption with a full pass-through of the tax burden to consumers. Additionally, only the welfare impact on the consumption side is measured in the scope of this study, excluding possible welfare benefits received from reduced emissions. However, these assumptions are reasonable given the structural stability in the short-term, as input reallocation is unlikely due to its requirements of new technology and time adjustments. Despite these outlined limitations, the analysis nevertheless provides useful policy insights and the best available estimates, which incorporate behavioral responses, on the effects of a carbon tax on consumption in Thailand.



	Bangkok	Central	North	Northeast	South
Without	0.3%	0.9%	1.4%	1.3%	0.7%
Transfer	0.1%	0.2%	0.0%	0.0%	0.3%
Pension	0.1%	0.1%	-0.6%	-0.7%	-0.1%
Food	0.1%	0.2%	0.2%	-0.3%	-0.1%
Taxcut	0.0%	0.4%	1.0%	1.1%	0.5%

Fig. 3. Effects of a carbon tax on poverty incidence by regions.

7. Conclusions

Over the past two decades, developed and developing countries have witnessed the increasing importance of energy and climate policies. Despite the growing amount of literature on the economic and environmental impact of energy and climate policies, only a few attempts have been made to conduct empirical studies of distributional aspects of these policies using microdata from household surveys in Thailand. The distributional incidence of carbon or energy taxation on households can influentially determine the impact of such policies on social objectives, such as reducing income inequality and poverty rates. These impacts can be very relevant to the public and political acceptance of a carbon tax, as well as to the design of appropriate policies. The novelty of this study is to inform carbon tax policy design in addressing the following three aspects of policy concerns: *Effectiveness, Equity and Social*.

For the *effectiveness* aspect, the demand estimation results indicate that pricing policy (e.g., through carbon taxation) is likely to be ineffective in reducing energy consumption in the residential sector as the energy demand is inelastic. Households are more responsive to reducing their consumption of transport fuels than electricity consumption when price changes. The findings suggest that the impact of changes in prices induced by a carbon tax may be more effective in reducing transport fuel consumption than electricity consumption, so other policy instruments should be further examined to reduce electricity consumption in the residential sector. Further studies should focus on the knowledge of the demand side to better understand the relationship between residential energy expenditure and household variables (Besagni and Borgarello, 2018). For example, household dwelling and demographic characteristics such as household size (Filippini and Pachauri, 2004) could play a major role in reducing electricity consumption, and demographic policies designed to change household circumstances such as household size and dwelling characteristics may be more effective in reducing electricity consumption and have positive environment impacts (Longhi, 2015).

For *equity and social* aspects, the results support the hypothesis that a carbon tax could be progressive in developing countries compared to a general finding of the regressive results in developed countries. The distribution of total aggregate welfare loss as a result of the carbon tax is more concentrated in households at higher income groups in Thailand. Concerns about the negative impact of environmental taxes on social development measures, such as income inequality and poverty incidence, should be downplayed as the results of this research indicate a carbon tax would have a minimal impact on income inequality and poverty rates in Thailand. The simulation of carbon tax imposition with revenue-recycling options indicates that using only partial amounts of the carbon tax revenues as lump-sum transfers to households can mitigate negative effects on income inequality and poverty incidence.

Given the concern regarding the potentially high burden of a carbon tax on low-income households and the low responsiveness of households to changes in electricity prices, the exemption of a carbon tax on natural gas, which is the main fuel used in the electricity sector, might be considered in Thailand. Such a policy was applied in Mexico for its initial introduction of a carbon tax in 2014 (ICAP, 2018). This exemption would be justified on the grounds that natural gas is cleaner energy compared to other fossil fuels, and the cost of electricity would have a larger impact on low-income households.

This study assumes no reallocation of input and, hence, excludes potential effects on the income side (i.e., changes in wages and employment), as well as health and welfare benefits from reduced emission levels. Tradeoffs between environmental targets, economic growth, and distributional effects require further study to combine disaggregation of households into a general equilibrium analysis. To support the arguments favoring carbon pricing in the work of Baranzini et al. (2017), policymakers should not consider the distributive impacts of a carbon tax policy from only an angle of equity, but further studies on the beneficiaries of reducing emissions, particularly future generations, should also be taken into account in the political economy of climate mitigation policies.

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Appendix

A. Literature review on distributional studies of a carbon tax

See Table A1.

B. Econometric specification of the QUAIDS model

For econometric specification, a number of techniques are employed to obtain unbiased parameters. First, the heterogeneity through observed demographic variables enters the demand system through α_i in the form of linear combination set of demographic variables z, $\alpha_i = \alpha_i(z)$ following Pollak and Wales (1981) to allow demographic factors to affect both the intercept and the slope of the budget share equations, linearly in the intercept term and nonlinearly in all expenditure terms through the first price aggregator, $a(p)$. Second, potential biases from endogeneity in expenditure could be solved by using an instrumental variable (IV) method and augmented regression techniques (Hausman, 1978) as employed in the work of Blundell and Robin (1999). The predicted residuals $(\hat{v})$ from the reduced form equation is augmented in the QUAIDS specification as another explanatory variable. The econometric specification of the QUAIDS model are therefore in the form of

$$w_i = \alpha_i(z) + \sum_{j=1}^{k} \gamma_{ij} ln p_j + \beta_i ln\left(\frac{m}{a(p,\theta)}\right) + \frac{\lambda_i}{b(p,\theta)}\left[ln\left(\frac{m}{a(p,\theta)}\right)\right]^2 + \rho_i \hat{v} + \varepsilon_i \tag{A.1}$$

where z represents a linear combination of demographic variables and θ is the set of parameters (e.g., α, γ, and β) which appears both in the price aggregator and on the right hand side of each budget share equation. The test for the significance of the coefficients of $\hat{v}$ in each budget share equation is equivalent to the direct test of the exogeneity of the expenditure variable. Meanwhile, the significance of λ provides the test for QUAIDS specification as opposed to the original almost ideal demand system specification or the presence of non-linear effects in budget share equations.

The non-linear equation systems of the QUAIDS model in Eq. (A.1) can be considered to have the conditional linear property. Blundell and Robin (1999) introduced the technique called the

Iterated Linear Least Square Estimator (ILLE) to be applicable for estimating the demand systems which possess the conditional linearity property. Following Lecocq and Robin (2015), a series of linear seeming unrelated regressions is performed within each iteration constraining for homogeneity while additivity is automatically satisfied and the symmetry constraint is imposed at a last estimation once convergence has occurred. The ILLE estimator $(\widehat{\theta})$ is asymptotically equivalent to the Non-Linear Three Stage Least Square class of estimators and the standard errors of all parameters are simultaneously obtained using the asymptotic variance-covariance matrix taking into account the predicted $\widehat{v}$ and the correlation of the error terms across equations (Blundell and Robin, 1999; Lecocq and Robin, 2015). Table B1 provides descriptions of variables used to estimate Eq. (A.1). The parameter estimates of the QUAIDS model are reported in Table B2.

Table A1
Summary of distributional impact of environmental taxes

Author (Year)	Country	Distributional impact
Symons et al. (1994)	The UK	**Regressive**: The incidence of carbon taxes reduces disposable expenditure (total expenditure less indirect tax payment) in the range of 7%–15%.
Hamilton and Cameron (1994)	Canada	**Moderate regressive**: The incidence of a carbon tax on household consumable income ranges from US$552 to US$645 per household on average, representing 2.3–2.7% of consumable income. The decrease in consumable income for the lowest quintile is about 1.1–1.2 percent larger than for the highest quintile.
Cornwell and Creedy (1996)	Australia	**Regressive:** The Gini inequality measure increases by 2.16% from 0.2778 to 0.2838.
Labandeira and Labeaga (1999)	Spain	**Inconclusive**: The carbon tax results in substantial equivalent losses in all household groups in the range of 2.7–3.35% of pre-reform expenditures. However, the regressive pattern is inconclusive from equivalent losses across total expenditure deciles.
Brännlund and Nordström (2004)	Sweden	**Regressive:** The incidence is more regressive when tax revenue is used to lower general VAT than to subsidize public transport. Under the lower general VAT case, the welfare loss (compensation variation as a percentage of disposable income) is 0.52% for lowest income quintile and 0.33% for highest income quintile. Under lower VAT on the public transport case, the welfare loss is 0.46% for the lowest income quintile and 0.40% for the highest income quintile
Wier et al. (2005)	Denmark	**Regressive:** The regressive incidence decreases when using total expenditure instead of income. Tax payment by low-income households was 0.8% of disposable income compared to 0.3% paid by high-income households
Tiezzi (2005)	Italy	**Progressive:** The poorest group of families had a welfare loss of 0.2% during the four years of carbon tax simulation compared to 9.2% loss for the richest group of families. However, the families in the second richest group tend to have the greatest welfare loss of 41.2%
Creedy and Sleeman (2006)	New Zealand	**Unambiguous**: The welfare loss (equivalent of variation divided by total expenditure) is generally around 1.4% of total expenditure, slightly more regressive among non-smoking households but ambiguous for the majority of households (categorized by family decomposition). The weekly tax payment increases in the range of NZ$ 2.86–14.89 and generally increases with size of household and level of total weekly expenditure.
Brenner et al. (2007)	China	**Progressive**: The lowest decile pays 2.1% of their total expenditures into the charge (i.e., carbon tax), and the highest decile pays 3.2%. Meanwhile, urban households pay an average of 3.3% (in the range of 3.2–3.5%) of their expenditure while rural households pay only 2.0% (in the range of 1.8–2.1%).
Kerkhof et al. (2008)	The Netherlands	**Regressive:** Tax burden is higher for low-income households (7% of income) than high-income households (4% of income).
Callan et al. (2009)	Ireland	**Regressive**: On average, weekly expenditure reduces in the range of €3.5–5.5per week across all income deciles. Meanwhile, rural households bear larger weekly expenditure of €2.5–6.5 per week compared to an increase of approximately €2.5–3.5 for urban households
Feng et al. (2010)	the UK	**Regressive**: CO2 tax results in 6% tax burden as share of income for the lowest income group and the highest income group would only pay about 2.4%. The regressive impact is less under the GHG tax scheme than the CO2 tax scheme.
Mathur and Morris (2014)	the USA	**Regressive:** The direct tax burden using expenditure as welfare measure for the bottom decile is 1.52%, which is about 3 times larger than 0.6% welfare reduction in the top decile. However, the indirect burden ranges from 0.60 to 0.69%, depicting a slightly progressive pattern.
Jiang and Shao (2014)	Shanghai (China)	**Regressive**: Low-income group bears the tax payment of 0.829% share of total expenditure while the tax burden share of the high-income group is 0.68%.
Agostini and Jiménez (2015)	Chile	**Slightly progressive:** The positive value of the Suits Index indicates that the gasoline taxes in Chile are slightly progressive.
Chen et al. (2015)	China	**Regional redistribution of wealth:** The carbon tax could lead to significant wealth redistribution or could be a corrective measure to redress the balance between poorer and richer provinces.
Renner et al. (2018)	Mexico	**Mixed effects:** A carbon tax on motor fuels has progressive effects, but regressive effects in taxing electricity, gas and public transport.

Table B1
Descriptions of variables

Variables	Type	Description
lny	Continuous	Log of monthly disposable income
lnx	Continuous	Log of monthly non-durable expenditure
w1	Continuous	Share of electricity
w2	Continuous	Share of transport fuels
w3	Continuous	Share of food and non-alcohol beverages
w4	Continuous	Share of other non-durable expenditure
lnp1	Continuous	Log of price indices for electricity
lnp2	Continuous	Log of price indices for transport fuels
lnp3	Continuous	Log of price indices for food and non-alcohol beverages
lnp4	Continuous	Log of price indices for other non-durable goods and services

(continued on next page)

Table B1 (*continued*)

Variables	Type	Description
nyg	Continuous	Numbers of young members with age less than 15 years old
noyg	Continuous	Numbers of adult members with age more than 15 years old
ownveh	Continuous	Numbers of owned vehicles i.e., automobile, pickup and van
oele	Continuous	Numbers of owned large electrical appliance i.e., microwave oven, refrigerator, washing machine and air conditioner
male	Dummy	Male headed (=1); Female headed (=0)
noneco	Reference	Households mainly earn income from non-economic activities (=0)
farm	Dummy	Households mainly earn income from farm operation (=1)
employ	Dummy	Households mainly earn income from wages and salaries (=1)
bus	Dummy	Households mainly earn income from non-farm business (=1)
BKK	Reference	Living in the Bangkok and metropolitan area (=0)
C	Dummy	Living in the Central region (=1)
N	Dummy	Living in the North region (=1)
NE	Dummy	Living in the Northeast region (=1)
S	Dummy	Living in the South region (=1)

Table B2
Parameter estimates of the QUAIDS model

Parameters	Electricity	Tfuels	FB	Others
gamma_lnp1	0.0167***	0.00365***	−0.00533**	−0.0150***
	(0.0005)	(0.0013)	(0.0027)	(0.0027)
gamma_lnp2	0.00365***	0.0328***	−0.0113***	−0.0252***
	(0.0006)	(0.0017)	(0.0035)	(0.0035)
gamma_lnp3	−0.00533***	−0.0113***	0.0282***	−0.0116***
	(0.0003)	(0.0009)	(0.0020)	(0.0020)
gamma_lnp4	−0.0150***	−0.0252***	−0.0116***	0.0518***
	(0.0004)	(0.0012)	(0.0025)	(0.0026)
beta_lnx	−0.0160***	−0.0538***	−0.121***	0.191***
	(0.0005)	(0.0013)	(0.0027)	(0.0027)
lambda_lnx2	−0.00118***	−0.0212***	−0.00852***	0.0309***
	(0.0001)	(0.0004)	(0.0008)	(0.0008)
rho_vexp	−0.00562***	−0.00559***	0.0178***	−0.00662***
	(0.0003)	(0.0008)	(0.0018)	(0.0018)
alpha_nyg	0.000333***	−0.00158***	0.0354***	−0.0341***
	(0.0001)	(0.0002)	(0.0004)	(0.0004)
alpha_noyg	0.00198***	0.00272***	0.0246***	−0.0293***
	(0.0001)	(0.0002)	(0.0004)	(0.0004)
alpha_ownveh	(0.0001)	0.0582***	−0.0341***	−0.0239***
	(0.0001)	(0.0003)	(0.0007)	(0.0007)
alpha_oele	0.00707***	0.000401**	−0.0126***	0.00515***
	(0.0001)	(0.0002)	(0.0004)	(0.0004)
alpha_male	−0.00121***	0.00637***	0.0105***	−0.0157***
	(0.0001)	(0.0003)	(0.0007)	(0.0007)
alpha_farm	−0.00495***	0.0261***	0.0107***	−0.0319***
	(0.0002)	(0.0005)	(0.0011)	(0.0011)
alpha_employ	−0.00302***	0.0204***	0.0227***	−0.0401***
	(0.0002)	(0.0005)	(0.0010)	(0.0010)
alpha_bus	0.00306***	0.00823***	0.0214***	−0.0327***
	(0.0002)	(0.0005)	(0.0011)	(0.0011)
alpha_C	−0.00495***	0.0210***	0.0178***	−0.0339***
	(0.0003)	(0.0008)	(0.0016)	(0.0016)
alpha_N	−0.0135***	0.0261***	0.0118***	−0.0244***
	(0.0003)	(0.0008)	(0.0017)	(0.0017)
alpha_NE	−0.0161***	0.0277***	0.0290***	−0.0406***
	(0.0003)	(0.0008)	(0.0017)	(0.0017)
alpha_S	−0.00984***	0.0353***	0.0131***	−0.0386***
	(0.0003)	(0.0008)	(0.0017)	(0.0017)
alpha_cons	0.0102***	−0.0278***	0.246***	0.771***
	(0.0006)	(0.0016)	(0.0035)	(0.0035)

Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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