CHIPS
Climate Change Impacts and Policies in Heterogeneous Societies

DELIVERABLE D3.2. Microsimulation results of distributional effects of climate impacts taking into account individual heterogeneity in demand responses

Jose M. Labeaga
UNED

JPI Climate AXIS

MARCH 2023

Introduction

Each day more, public policy design and implementation requires evidence to make decisions because of reasons as better employing public resources, understanding the results of the policies, or targeting policy interventions to affected individuals. The more and better evidence we have, the better we will evaluate the impact of the policies or the adequate distribution of the resources, being the fulfilment of their objectives a matter of ex – post (or impact) evaluation or ex – ante evaluation (microsimulation).[1]

Microsimulation models are tools increasingly used to evaluate the effect of a policy or a reform on a representative sample of individual agents (households, consumers, taxpayers, etc.).[2] Then, it is a micro-based methodology either deterministic or stochastic, which allows computing both aggregate and distributional effects of a policy, reform (changes of rules) or shock, considering the heterogeneity among individuals. Therefore, they constitute a powerful tool for the development of decision-support models to simulate and evaluate the impact of public policies. Since the estimates are at the microlevel, the instrument allows computing outcomes and effects both at individual and aggregate levels.

This report attempts to present some antecedents, the current development, and new ideas in the microsimulation literature. These tools have been proposed for the study of different questions reforms involving changes in prices and/or incomes of the individuals. The aim of the report is to present the main features of the tool developed in the CHIPS project and illustrate its capabilities using simple examples of exercises conducted with it.[3]

Spurred by the availability of micro data and computer power, the use of microsimulation methods to perform ex-ante and ex-post evaluation of policy reforms is becoming more and more widespread. Microsimulation techniques can contribute to current policy debates and, especially when it comes to modelling behavioural responses triggered by reforms or events, they have attracted a lot of attention both from the academic community and policymakers. In words of O'Donoghue (2021), "*microsimulation is a mechanism of abstracting from reality to help us understand complexity better*". He quotes three kinds of complexity related to the population structure, the policy (shock) structure and the behavioural response to the policy.

Microsimulation models allow morning-after (first-round) aggregate and distributional effects of reforms to be simulated. It allows a wide range of reforms stemming from changes in the parameters or regulations (either tax code or any other kind of regulation), in the absence of any behavioural reaction by agents. A microsimulation model for indirect taxation, for instance, allows changes in the value added tax and excise duties to be simulated. In addition to morning-after effects, it captures the behavioural response to the policy of households through the previous adjustment of responses by estimating a demand system. Therefore, in addition to first-round effects, the tool allows households' behavioural reaction to price changes stemming from policy changes (second-round effects) to be

[1] The original contribution of impact evaluation in economics is dated back to Heckman et al. (1997). Issue number 4 of the Review of Economic Studies where the paper was published corresponds to a special issue collecting a subset of papers presented at a Conference on Evaluation of Training Programmes held on 10-11 September 1993 at CEMFI, Madrid. Microsimulation modelling (ex – ante evaluation) is dated back to Orcutt (1957, 1961). A nice recent example of its potential can be seen in De Agostini et al. (2018).

[2] See, for instance, O'Donoghue (2021).

[3] An example of its potential is described in the index of the recent book by O'Donoghue (2021). It covers matters as evaluation of anti-poverty policies, tax reforms and redistribution, labor supply behavior, consumption behavior and indirect taxation, environmental taxation, intertemporal decomposition of changes in inequality, pension reforms and life-course distribution or spatial inequality and poverty. Other monographs containing theory and examples of the use of microsimulation models to different economic research themes are Harding and Zaidi (2009) or Spadaro (2007).

predicted. Models for simulating changes in income of prices (taxes or inflation) both provide a comprehensive evaluation of changes, by accounting for the effects relating to tax collection, effective tax rates, winners and losers, inequality indices or poverty measures. These effects can be disaggregated by a wide set of variables as income decile, location of the household, age group and many other. Moreover, if the model incorporates behavioural responses, it can provide results for individual as well as social welfare changes.

Most of the questions related to policies, shocks or events we are interested in answering fall in one of the following categories:

1. Changes in size and structure of public spending (who has the right for receiving a transfer, which good is going to be subsidized, …)
2. Changes in prices (because of taxation or other reasons)
3. Structural reforms (introduction of a social security system of a pension reform)
4. Changes in the macro framework such as the fiscal, inflation, and other kind of targets
5. Exogenous shock, i.e., lockdown, extreme events, …

The previous questions could be associated with different perspectives about fighting against inequality or poverty. We can address the first two categories using microeconomic tools and, in terms of simulating policies, either a non-behavioural or a theory-based model is adequate. Standard incidence analysis of public spending and taxation are the two components of the toolkit to be use in the microeconomic adjustment and the microsimulation exercise. The following three questions refer to three kinds of macro policies, which, of course have consequences for the individuals. The first macro policy is concerned with policy-induced changes in the structure of the economy, either in terms of sectoral activity or price policies (whether necessary services are provided by private versus public offer, for instance). The fourth category includes, again, questions of aggregate demand (the country-target of inflation) with strong potential distributional consequences. The last one is a kind of *drawer of tailor's box*, which is not usual to find in economic modelling, but it has many consequences for private investment, private (and public insurance), growth and then, for redistribution.

To address questions of the nature of the first two and their implications for inequality and poverty, we can rely on a microsimulation module based on household micro data. It allows assessing the distributional incidence of changes in prices (taxes), and even combine all goods (leisure included) to analyse the effects on employment – unemployment levels in the labour market. An intermediate solution should include tools, on one hand, generating disaggregated inputs (predictions) obtained at an aggregate level (effects on GDP, for instance, which can be expressed for different sectors and different types of households) taking as inputs to be used to produce results at the microsimulation tool. These second alternative still generates first-round effects, except for the case we iterate several times through the process. The last alternative includes aggregate macro-modelling tools (a Computable General Equilibrium -CGE- model) that permits evaluating the impact of exogenous shocks and policies on aggregates like GDP, its components, the general price level, and the like, either in the short-run or in a long-run growth perspective.

Then, poverty and/or inequality analysis can be performed either in the context or partial equilibrium, i.e., we are only interested in the so-called first-round effects, or in the context of general equilibrium, i.e., considering direct and indirect effects of policies or events. In CGE models, these evaluations can be performed in several ways. The simplest but least desirable method uses an *elasticity* calculation for poverty (inequality) given changes in household consumption (income-wealth) either per-capita or using some equivalent scale. Representative- household or survey-based microsimulation approaches are preferable. The former assumes fixed distributions of income or consumption within each household group, providing welfare estimations directly from the CGE model results. The latter type of approach does not need to recur to the rather stringent assumption of fixed within-group income distributions. It can be either top down, feeding CGE simulation results to a household model, or integrated, with the household model built directly into the microsimulation tool.

The tool we are presenting has numerous drawbacks as the various monographs previously quoted have emphasized. Although we think that the main problem for the use of the tool is the unavailability of adequate data to answer questions posed by policies, shocks or events, abstracting from reality simplifies the model and it allows simple explanations of policy effects at the cost of introducing many simplifying assumptions. Even in the case of an economic model, there are many relationships among variables for the policy to produce complex effects that partial equilibrium models are unable to answer. Even combining the microsimulation tool with input-output tables collecting the functioning of the production sector, or incorporating a CGE module, some problems arise even for making them compatible since many times we are going to produce variables at the level of disaggregation needed to run the microsimulation tool. Another limitation comes from the *caeteris paribus* assumption. When running a simulation, even if the policy or shock does not affect a particular variable, the horizon of the simulation makes necessary to adjust economic or sociodemographic variables that do not remain constant. For instance, an extreme event could induce migration from locations affected to alternative locations, thus affecting economic variables as labour supply, income, prices or any other variables in the two regions. An adequate simulation requires adjusting populations and the rest of variables. Finally, there are several sources of uncertainty different from the previous related problems, and we need to consider them in our microsimulation exercises.

The rest of the report is organized in four sections. In Section 2, we revise the literature of standard microsimulation models with a specific view of those applied to demand – consumption analysis. Although the literature on labour supply has been very prolific in using this kind of models, we can see it as the reverse of a demand model since modelling labour supply is equivalent to modelling leisure. In Section 3, we summarize the usual way to run microsimulation models as the one we have employed during the development of the CHIPS project. Section 4 is devoted to describing some problems in employing these models. These deficiencies arise either from data, modelling, or type of results. Trying to solve all these problems either individual or jointly, we revise some suggestions both from the literature as well as some new proposal, which could be useful in the future depending on data availability. Section 5 concludes.

Revisiting the literature on microsimulation models

This section describes the literature on micro-simulation models of the type we employed to assess the effects of proposed changes in environmental taxation. The main results of this microsimulation are also presented here, with an explicit calculation of the impact of carbon taxation on aggregate government receipts, CO_2 emissions, monetarized environmental benefits and the distribution of burdens across households.

The microsimulation procedure is based both in the assumption of non-behavioral responses by households or the existence of some theory-based model where those responses are specified and estimated. The first simply assumes that the effects of any change in prices or income is going to be translated as morning-after effects. The second establishes that the households are going to react to the shock. In both cases, we compute the effects using microdata both for Spain and Mexico, but we must note that the only restriction to be applied to any country is the availability of household budget surveys in the first case and both availability and adjustment of behavior in the second.

As mentioned in the introduction, microsimulation models in the social sciences were pioneered by Guy Orcutt in the late 1950s and early 1960's (Orcutt, 1957; Orcutt, 1961 or Orcutt et al., 1961). This kind of tools is commonly applied to areas of public policy-relevance such as labour supply or demand for health and health care (see the monographs by Mitton et al., 2000; Spadaro, 2007; Harding and Zaidi, 2010 or O'Donoghue, 2021). In this report we consider an approach that mainly address questions related to the effect of policies (shocks) affecting income and prices. Here, we relate those policies to energy or environmental issues to the effects of introducing policies trying to mitigate climate change. The pioneering works trying to evaluate the effects of social or economic public policies were arithmetic, thus, they basically re-calculate the economic variables needed at outcomes to be evaluated by the policy for each statistical unit of the sample (either individual or household) using a representative dataset under different hypothetical scenarios. Since these are evaluation tools, their intention is to answer "what if" questions about the effects of introduction of specific policies or occurrence of potential shocks on household income of each statistical unit and hence on the overall income distribution, and on aggregate variables.

The usual categorization of microsimulation tools is normally as non-behavioural (static) or behavioural (dynamic) as explained, by example, in Harding (1996). The static models assume that all the variables other than the outcome remain at the pre-policy (pre-shock) values and they apply purely deterministic changes on the data. Dynamic models adjust statistical units changing values of the variables affected by the adjusted behaviour (Li and O'Donoghue, 2013). Adjusted behaviour means that we normally use microeconometric models of individual preferences to estimate the effects of policy changes on behaviour, in our case in terms of demand for goods.

The sense we give to microsimulation tools is as part of the policy evaluation literature, i.e., an alternative methodology to provide evidence-based evaluation. Since we normally use it ex-ante, the results can be used for the design of policies or norms. However, the policy evaluation literature has been more focused on ex-post studies (see Heckman et al., 1997), but Blundell (2012), among others, have underlined the need to consider both ex-ante and ex-post methods to analyse the effects of policy changes. In this context, our proposal can offer insights in two ways since microsimulation tools can do ex-ante analysis through the simulation of the counterfactual scenarios reflecting alternative policy options. In addition, microsimulation features in the strand of literature that involves links between the microeconomic and macroeconomic sides, since the tool allow to simulate macro-policies, but also evaluate the impact on aggregate variables looking at distributional effects.

In the last thirty years there are a great number of examples where the literature on microsimulation has expanded as the several monograph studies already mentioned show. Moreover, in 2005 was established the International Microsimulation Association (IMA) and since 2007 the International Journal of Microsimulation under the auspices of the IMA collects the latest developments in the field.[4]

The components of the CHIPS microsimulation model

The demand component

We base our simulations on the existence of economic relationships concerning the demand for goods. We try to adjust the behaviour in a structural way understanding that the parameters are going to be valid except if some structural change occurs.[5] Moreover, we need to assume that any policy, shock, or event is not going to affect the estimated parameters (our model does not suffer the Lucas critique, Lucas, 1976). It is very easy to run simulations without imposing the parameters. Using these two

[4] See http://www.microsimulation.org/ijm/.

[5] The COVID-19 brought about a structural change in household demand patterns because some goods could not be consumed for a period. In addition, some sectors were affected in employment so that workers experienced reductions in their labor income even after the transfers that governments introduced for the duration of the lockdown. These changes in behavior also had their effects on the aggregate magnitudes of the economy of all countries.

different methodologies allows evaluating the importance of behaviour adjustment. The results of the second microsimulation method are named morning-after or first-round effects, while those under behaviour could be interpreted for longer periods.

To estimate the parameters of the demand model, we have proceeded in several steps. All systems we estimate allow for quadratic effects (i.e., demand systems of rank three) to allow for flexible income responses. So, we base our theoretical model on the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980) and the Quadratic Almost Ideal Demand System (QUAIDS) of Banks et al. (1997).[6] The QUAIDS assumes the following cost function:

$$\ln c(u,p) = \ln a(p) + \frac{\ln u \, b(p)}{1-\lambda(p)\ln u} \quad [1]$$

where *u* is utility, *p* is a set of prices, *a(p)* is a function that is homogenous of degree one in prices, *b(p)* and *λ(p)* are functions that are homogenous of degree zero in prices. Accordingly, the indirect utility function is:

$$\ln V = \left\{ \left[\frac{\ln m - \ln a(p)}{b(p)} \right]^{-1} + \lambda(p) \right\}^{-1} \quad [2]$$

where *m* is total expenditure, *ln a(p)* and *b(p)* are the translog and Cobb-Douglas functions of prices defined as:

$$\ln a(p) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln p_i \ln p_j \qquad b(p) = \prod_{i=1}^{n} p_i^{\beta_i} \quad [3]$$

where p_i and p_j are price indices of goods *i* and *j*, respectively. $\lambda(p)$ is a differentiable, homogenous function of degree zero in prices, and defined as $\lambda(p) = \sum_{i}^{n} \lambda_i \ln p_i$.

The model we estimate is expressed in expenditure shares for each of the goods within total non-durable expenditures as shown in equation [5]. We derive these equations by applying Shephard's lemma to the cost function [1] or Roy's identity to the indirect utility function [2]. As usual, the demand should satisfy additivity of budget shares, homogeneity of price responses and Slutsky symmetry. We impose additivity by omitting one equation out of the system during the estimation. Homogeneity in single equations is imposed by expressing prices in relative terms to the excluded good. System-homogeneity and Slutsky symmetry concern the whole demand system and cannot be imposed, but we test for them after estimation.[7]

[6] Details about these two demand models are provided in Deaton and Muellbauer (1980) and Banks et al. (1997) and we omit the details in this report.

[7] The demand system and its estimation show many additional features concerning the demand for some energy goods. For instance, we observe some groups (energy for transport is the classical example in our context) reporting a non-negligible proportion of zero expenditures. The literature shows (see for instance Labandeira et al., 2006) that they correspond mainly to non-participants, i.e., individuals (households) who do not own a vehicle. We leave estimation details out of the scope of this report.

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_i}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}^2 \quad [5]$$

where w_i is the budget share of the non-durable good i ($i = 1, \ldots, K$) and α, γ, β, and λ are parameters to be estimated. In the estimation of the demand system, we let the parameters incorporate a wide range of household and individual demographic characteristics allowing heterogeneity to affect demand and implied elasticities. In this sense, the intercept α_i can be expressed as $\alpha_i = \alpha_i(Z_h)$ being Z_h a vector of explanatory variables of household h.[8]

The microsimulation tool

With the parameters estimates at hand, our simulation procedure is as follows: First, we calculate the new demand shares in 2018 (in the case of Mexican data or 2019 in the case of Spanish data) using the parameters obtained from the estimation of the demand model and the new prices (new income). With the new expenditure shares, if we assume total expenditure on durable goods remains unchanged, we obtain the new expenditures on the different goods considered. Dividing the expenditure shares on the different energy products before and after the change in prices by their average price in 2018 (2019) we obtain the consumption before and after the change in prices, which allows us to evaluate their impact on any good and, in particular, on energy consumption and associated emissions (using the emission factors), as well as the additional revenue generated by the application of the new prices, even if taxes do not change.

In the case of a change-in-price (or tax) policy, the microsimulation model calculates the taxes (Value Added Tax and any excise duty) paid by each household. Of course, this can be done either without allowing the behavioural reactions of households to changes in prices and income, but also introducing responses. Therefore, in addition to first-round or morning-after effects (defined as changes keeping each household's expenditure constant for each commodity) we can estimate second-round effects arising from demand adjustments. This adjustment is allowed in the form of substitution between commodities, subject to a constant total level of consumption of non-durable goods.[9] In the case of changes in income, its effects could be passed on to total consumption, including durables, or only to non-durable consumption. However, to be theoretically consistent, our model only allows changes in income affecting the consumption definition of the model.

The way we perform the calculation of the variables affected by the change in prices (or income) starts by calculating the pre-change tax payments on VAT and excise duties for each household from its expenditure on non-durable goods. We aggregate household tax payments using the grossing-up factors (number of households in the population represented by each household in the sample) to obtain the initial revenue got by the government ($\boldsymbol{R^0}$):

$$\boldsymbol{R^0} = \left[\sum_{h=1}^{N} g_h \sum_{k=1}^{K} \frac{t_k^0 p_{kh}^0 q_{kh}^0}{1+t_k^0}\right] \quad [6]$$

[8] It is also possible to introduce heterogeneity through the rest of the parameters of the model. Details about this and other theoretical issues as well as explicit derivation of the own-price, cross-price and income elasticities are in Banks et al. (1997) or for the case of an energy demand system in Labandeira et al. (2006).

[9] We can integrate durable goods in the model and run simulations for total expenditure both on durables and non-durables. However, we consider that purchase of durables is more an investment than a consumption decision.

where the first sum extends to all households in the sample (*N*) and the second to all goods we consider (*K*). $\boldsymbol{t_k^0}$ is the pre-change tax rate of good *k* (for simplicity we assume it includes both the VAT and excise duty) and $\boldsymbol{p_k^0}$ and $\boldsymbol{q_k^0}$ are the pre-change price and pre-change quantity demanded, respectively. Post-change revenue can be calculated using [1] in the same way but substituting prices, quantities and tax rates by their post-change values. When behaviour is not considered, only prices and tax rates change, whereas $\boldsymbol{q_k^0 = q_k^1;\ \forall k}$.

The post-change tax payment of household *h* for good *k* is $\frac{\boldsymbol{t_k^1 p_{kh}^1 \hat{q}_{kh}^1}}{\boldsymbol{1+t_k^1}}$, with super-index 1 representing post-change values and $\boldsymbol{\hat{q}_{kh}^1}$ denotes the predicted value of quantity demanded for good *k* by household *h* The post-change revenue obtained by the government when behaviour is considered can then be expressed as:

$$\boldsymbol{R^1 = \left[\sum_{h=1}^{N} g_h \sum_{k=1}^{K} \frac{t_k^1 p_{kh}^1 \hat{q}_{kh}^1}{1+t_k^1}\right]} \quad [7]$$

Once we have the new shares (and quantities) we can calculate the impact of the change in prices (taxes) on energy consumption just comparing pre-change with post-change quantities and thus also the effects on CO_2 emissions. To obtain this last figure we use the initial amounts of gasoline and LPG using the average prices of these products in 2018 (in the case of electricity, the initial amounts are obtained when calculating the subsidy). The post-change prices and quantities serve us to calculate post-change emissions. In the two cases, we convert consumption to emissions using the emission factors from INECC (2014) for gasoline and LPG, and the IEA (2019) emission factor for Mexico for electricity. The information on the increase in tax revenue together with the grossing-up factor allows us to obtain the cash transfer that each household will receive in each of the cases where we consider recycling. The cash-transfer is added to the income of the household to get the new income variable, which we then use to calculate the new equivalent income (and be able to calculate distribution measures and indexes) and the new poverty rate. To calculate food and energy poverty rates we need to use the new household income and the new expenditures on food and energy at new prices imposed by the estimated demand system.

We would also be interested in providing some welfare measure arising from the reforms, as well as some indexes describing distributional effects. Despite the various conceptual drawbacks fully described in Banks et al. (1996), the change in household welfare is quantified through the equivalent gain, a money-metric impact of price changes and/or income changes. An equivalent gain (loss) is the amount of money that needs to be subtracted from (given to) the household to attain the pre-change level of utility at final prices. We follow the method of King (1983) in computing this measure, although adapting it to the QAIDS, in a similar way to Thomas (2022). In this sense, we evaluate the equivalent loss (gain) for the case of a price change as:

$$\boldsymbol{EL^h = c(u_0, p^0) - c(u_0, p^1)} \quad [8]$$

where $\boldsymbol{u_0}$ is pre-change utility, $\boldsymbol{p^0}$ and $\boldsymbol{p^1}$ are the vector of pre- and post-change prices, respectively, $\boldsymbol{c(u_0, p^0)}$ the observed pre-shock expenditure and $\boldsymbol{c(u_0, p^1)}$ the equivalent income, i.e., the expenditure level at pre-change prices that is equivalent in utility terms to household expenditure at final prices. We calculate it from the expenditure function [1], using the parameters estimated in the demand model and the prices before and after the price (tax) change. The level of utility before the change in prices (income) is calculated in [2] using the prices before the change. To see the net distributional impact of the price changes we consider the index of Reynolds and Smolensky (1977).

Finally, we can calculate the Gini index before and after the change in prices to evaluate their effect on inequality.

The data

We do two exercises inside CHIPS to apply the microsimulation tool. One uses data of the Spanish Household Budget Survey (Encuesta de Presupuestos Familiares) and another data from the Mexican Household Budget Survey. We are lucky to have available Mexican survey data for a long period to be able to do the process explained in our microeconomic-microsimulation framework. We illustrate an example for Mexico, where we have a bi-annual survey representative of the Mexican population, the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) produced by the Instituto Nacional de Estadística y Geografía (INEGI). It is a biannual survey that uses face-to-face interviews to collect household budget data using stratified random sampling. The survey collects information on the value of household expenditures on different goods and services, providing detailed information on household and housing characteristics (see INEGI, 2022a).

In the estimation step, we construct a sample of microdata for the period 2006-2018 from the ENIGH. The initial sample size is 251,437 observations for all the pooled biannual cross-sections. The characteristics of the data as well as our own objectives make us select the sample as follows. We drop households where several families live, households with no expenditure on food, no expenditure on non-durable goods and households with no income, as well as first top and bottom percentiles of the distributions of total non-durable expenditure and income. This process reduces the sample by 21,142 observations.

We use the following categories of expenditure:[10] food at home, low octane gasoline (magna), high octane gasoline (premium), liquefied petroleum gases (LPG), electricity, and other non-durable goods.[11] Since our aim is to estimate a flexible Quadratic Almost Ideal Demand System, we calculate the expenditure shares for each commodity by dividing the expenditure on it by the total expenditure on non-durable goods in the household. In the specification of the demand model, we include a wide set of sociodemographic variables (the Z vector previously defined) whose definitions and descriptive statistics are in Labandeira et al. (2022).[12]

We need price data with as much variation as possible to identify own and cross-price effects. We do have in the ENIGH survey information about the week where the interview took place. From this information, we create the variable month. The INEGI (2022b) considers the price indexes of different goods as well as the Retail Price Index (Índice Nacional de Precios al Consumo, INPC from now on) at monthly level in the cities.[13] INEGI provides price data for 46 cities for the whole sample period, which we assign to Entidades Federativas. We consider the monthly INPC for cities and we assign each household the price corresponding to the month when the survey was conducted. We consider the following nominal price indexes and the Retail Price Index (to construct and use real prices): food, electricity, LPG, magna gasoline, and premium gasoline. To complete a demand system, we add a

[10] All monetary variables, prices included, has been deflated using the regional Retail Price Index (RPI) to get variables in real terms. The tool can be adapted easily to accommodate any number of good with minor changes.

[11] Other non-durable goods include non-alcoholic drinks, alcoholic drinks, tobacco, housing goods for cleaning and caring, goods for personal care, newspapers, stationery not for education, oils, lubricants and additives, candles and candlesticks, other fuels (carboard, paper for burning, etc.), medicines and healing materials, materials for dwelling repairing, photographic material, expenses on gifts to people outside de household (food, drinks and tobacco), diesel and gas for housing, petrol, diesel for transport, wood, fuel for heating and natural gas.

[12] Important variables for the purposes of this report are geographical location of the household, both Entidad Federativa and municipality.

[13] INEGI also provides information for the INPC for Entidades Federativas, but they do it only from 2018, which we introduce.

category of other non-durable goods for which we do not have any information at city level (it implies that we cannot do the previous assignments to Entidades Federativas and municipalities), so the price of other non-durable goods is calculated as a weighted average of prices for alcoholic beverages and tobacco, detergents and similar products, drugs, personal care goods and services, newspapers, and other goods. The weights correspond to the share each household devote to each good.[14]

The scenarios for microsimulation

We consider several scenarios for simulation based on the introduction of a carbon tax. We introduce a CO_2 emissions tax on energy products covered by our model, using two alternatives, a tax rate of \$25/tCO_2 and a tax rate of \$50/tCO_2. To calculate the tax rates on each of the energy products we use the emission factors from INECC (2014) for gasoline and LPG, and CRE (2019) for electricity, as well as the OECD (2022) exchange rate, to express the tax rates in Mexican pesos. We consider 2018 prices of magna and premium gasoline from IEA (2019), as well as the price of LPG from SENER (2019), on which we apply the tax considered to obtain the corresponding price increase because of the reform, assuming full-pass-through to consumers. The results are presented in Table 4. In the case of residential electricity, as noted above, Mexican tariffs are heavily subsidized, so it is unrealistic to assume that the new tax on electricity will be fully passed on to consumers, so we assume that the 25(50) \$/tCO_2 tax will increase the residential price of electricity by 10(20) percent. The relative increase in prices under the two scenarios for electricity are 10 and 20 percent, for LPGs 10.49 and 22.17 percent and for gasoline are 5.73 and 12.13 percent.

Since our proposed reforms generate additional tax revenue, we use it to reduce poverty and inequality. To do so, we consider two compensatory schemes: a lump-sum transfer to all households and a lump-sum transfer targeted only to the poorest households (defined as those in the bottom three deciles of income.

Output of the microsimulation tool with an example using Mexican data

We assume that the carbon tax could either be 25\$ or 50\$ per CO2 ton. We follow the theory outlined in subsection 3.1 to adjust the behaviour of Mexican households and be able to translate the effect of this potential change to consumption and compute, among other variables and indexes, inequality and poverty measures. The way we translate prices to individuals is by imposing the adjusted behaviour in a way such that any household react to these price increases by adjusting demand of goods. Then, we can aggregate household responses since we have the grossing-up factor for each household (number of households in the population represented by each household in the sample).

Our first objective in this subsection is to show some output that the application of the CHIPS microsimulation model can produce with a real example using Mexican microdata. In this sense, we simulate the environmental, revenue and distributional effects of a CO_2 emissions tax on the main energy products as mentioned. Energy taxes have the capacity to generate a relevant volume of public revenue, sometimes at the cost of significant distributional impacts. So, our second aim is to explore the introduction of compensatory mechanisms aimed to reduce poverty and inequality using the additional revenue generated by the carbon tax. Countries such as Mexico that show significant problems of poverty and inequality are unlikely to suffer significant distributional problems, but the extent of pre-existing poverty is so significant that the introduction of compensatory mechanisms may still be very important. In 2018, the percentage of households living with less than 60 percent of

[14] Details of the whole process of assigning prices are in Labandeira et al. (2022) and some descriptives of shares and prices are presented in Table 1.

median income (the poverty line as defined by many authors as Heindl, 2015, for instance) and using household expenditure as a proxy for income. In our data, more than 23 per cent of households are in poverty, especially prominent in the south of the country (over 37 per cent of households in poverty) and in rural areas (almost 43 per cent). The Gini index shows that inequality is also higher in the south and in rural areas.

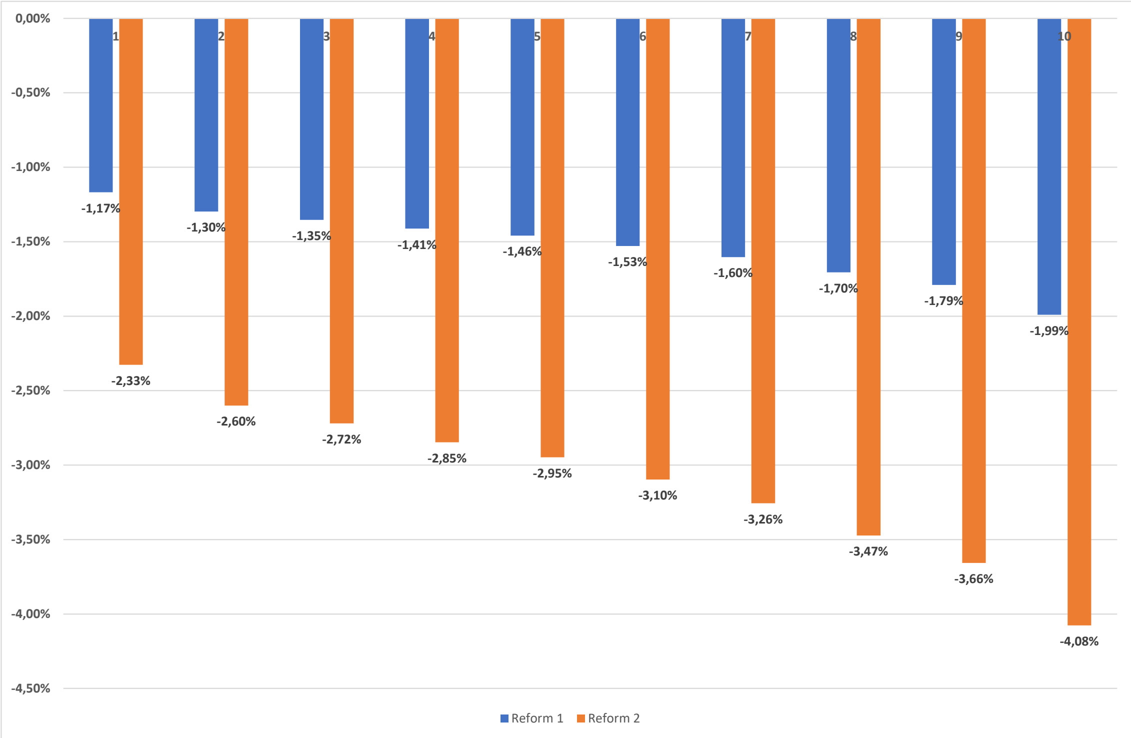
There are many reasons why Mexico is a good candidate to apply microsimulation models to study the effects of price or income shocks. Among them, we can quote, first, Mexico is a country very affected by tropical cyclones for which it would be very usual to produce policy parameters, i.e., income and price responses of the individuals (households) to be able to derive inequality and poverty elasticities. Second, Mexico albeit being part of the OECD is a middle-income country, which in any expected global compensation scheme is going to be part of the recipient group of countries given their climate risks. Third, among the commitments of the Paris Agreement, the signatory countries agreed to reduce their greenhouse gas emissions, translating this commitment into Nationally Determined Contributions (NDCs) and Mexico committed unconditionally to reduce its greenhouse gas (GHG) emissions by 22 percent in 2030 compared to the baseline constructed in a baseline scenario estimated for 2013 (991MtCO_2e). In addition, the Government of Mexico committed in to increase emissions mitigation to 36 percent in 2030 compared to the baseline scenario. Fourth, within Mexican GHG emissions, energy-related emissions stand out, accounting for 63.5 percent of gross GHG emissions and 87.5 percent of net emissions (including removals) in 2019, and then, it is crucial, to achieve significant reductions in the coming years, to design and implement public policies particularly for the energy sector. Fifth, Mexico initiated an energy reform before the Paris Agreement in December 2013, with the aim of substantially transforming the energy sector. This reform was far reaching by Mexican standards and entailed steps that were earlier considered unthinkable in Mexico such as the elimination of PEMEX's monopoly, as well as the modification of the mechanism for determining tax rates on gasoline (which often resulted in a subsidy), replacing it with fixed tax rates.

The introduction of a \$25/tCO2 tax on energy products would reduce their demand 5.10 percent, with associated CO_2 emissions reduction of 3.52 percent. The additional revenue obtained would be 27,800 million pesos. In terms of welfare effects, the reform would lead to an average equivalent loss of 1.53 percent, and it has a progressive impact, with the equivalent gain decreasing as the income rises (or equivalent loss increasing with income, Figure 1). This result is because the progressive impact of the increase in the price of gasoline more than offsets the regressive impact derived from the increase in the price of electricity. On the other hand, the impact of the price of LPG is progressive in the lower income deciles and regressive in the higher income deciles, because average LPG expenditure shares are increasing in the lower income deciles and decreasing in the higher income deciles.

Although the introduction of a carbon tax affects richer households more, it also harms some poor households, which see their energy costs increase, so the net distributional effect of the reform is unclear. Furthermore, the reform would increase the poverty rate (Figures 2 and 3), except in the south, where it would be very slightly reduced, as well as inequality, both at the national level and in each of the different areas considered. So, these first results justify the need to introduce compensatory schemes.

If the additional revenue is used to compensate all households through a lump sum transfer, each household would receive an annual amount of 888 pesos. This scheme would reduce inequality and the poverty rate with respect to the situation before the introduction of the carbon tax, both at the aggregate level and in the different areas considered. However, we can see that average reductions are not very large. On the other hand, if we introduce the scheme to compensate households in the three bottom deciles of income, each household will receive 2958 pesos per year and the measure would make it possible to achieve greater reductions in inequality and in the poverty rate. In both cases the Reynolds-Smolensky index would become positive (0.0024 and 0.0067, respectively), so that the compensatory package converts a regressive into a net progressive reform, while at the same time reducing inequality and poverty (Figures 2 and 3 for geographical area and urban-rural divide respectively).

Figure 1. Equivalent gain per income decile

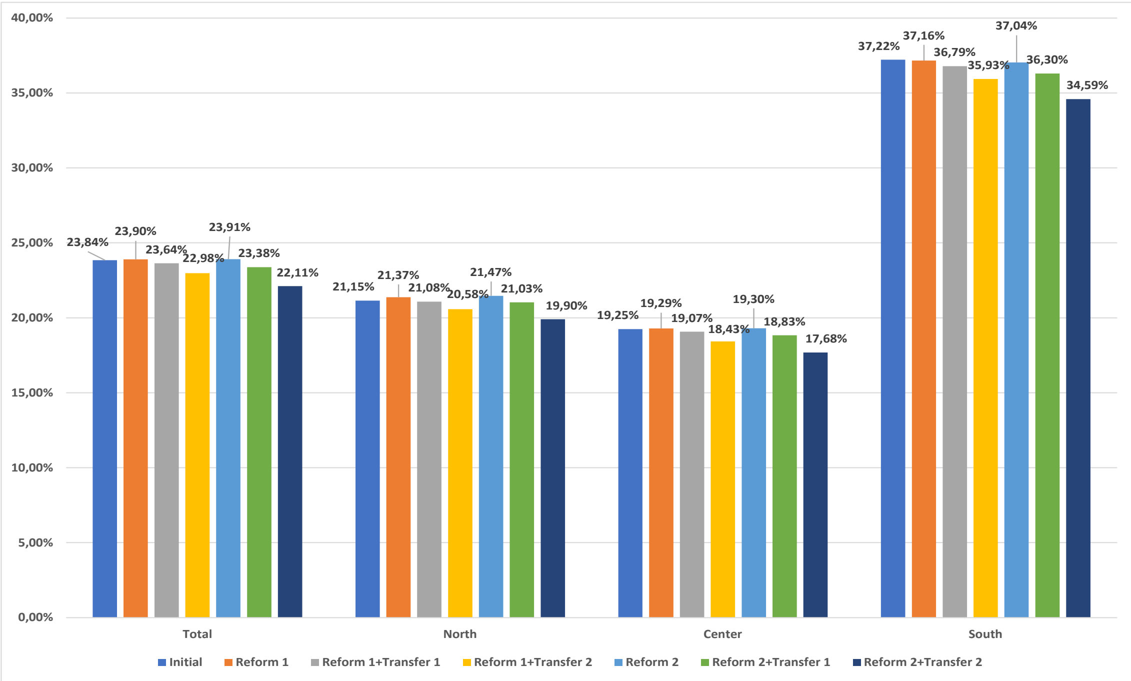


Note. Equivalent gain is defined as the percent of total non-durable expenditure.
Source: Own calculations

If instead of a carbon tax of \$25/tCO_2, we double the rate to \$50/tCO_2, the demand for the energy products considered would fall by 11.33 percent and the associated CO_2 emissions by 9.74 percent, generating an excess revenue of 54026 million pesos. The welfare impacts would be as expected of greater magnitude than in the previous simulation, with an average equivalent loss of -3.10 percent, although they would also be progressive, with an equivalent gain decreasing with income, due, once again, to the progressive impact of the increase in the price of gasoline, which offsets the regressive impact of the increase in the price of electricity.

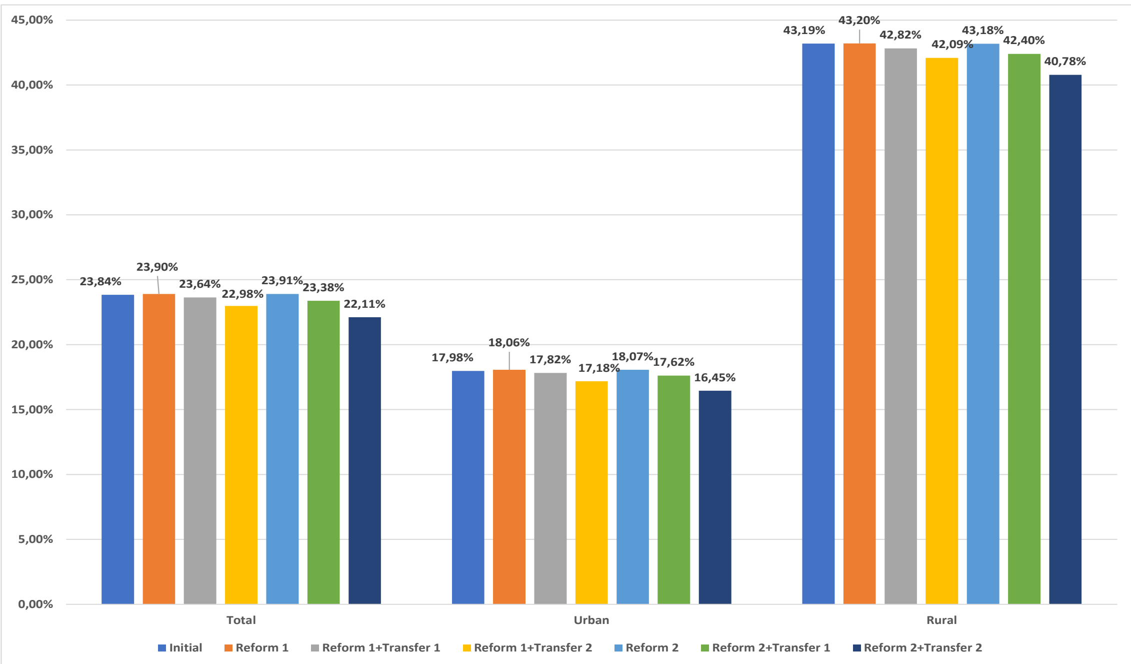
Anyway, this reform would also have a net regressive distributive effect (Reynolds-Smolensky of -0.0009) and would increase the poverty rate (except in the south, where it is slightly reduced, and in rural areas, where it hardly varies), increasing inequality in each of the areas considered to a greater extent, which justifies the application compensatory measures. In the same scenarios as before for the transfer schemes, now a lump-sum transfer to all households spending all additional revenue represents each household would receive 1726 pesos per year, while if the transfer is targeted only to households in the three bottom income deciles, each household would receive 5752 pesos per year. Again, with the compensatory schemes (and as before especially the second compensatory package) the reform would contribute to reduce inequality (reduction of the Gini index) and poverty, with a progressive net distributional impact (the Reynolds-Smolensky index with the compensations would be 0.0046 and 0.0129, respectively).

Figure 2. Poverty rate by geographical area



Source: Own calculations

Figure 3. Poverty rate by urban-rural divide



Source: Own calculations

Some problems of our microsimulation tool and proposed solutions

One of the first questions to consider when interpreting the results of microsimulation models is that they are provided with uncertainty, even in the case of adjusting non-behavioural responses. So, the first robustness check that deserves some attention is to give some sensitivity indication of the results to changes in the assumptions. For instance, one could think in providing lower and upper-bound estimates (see, for instance, Fankhauser, 1994). Of course, when the microsimulation tool employs estimates of demand, uncertainty could also come from the dispersion of these coefficients. Then, we have another change to produce sensitivity analysis of our results. The choice of whether to use a behavioural model depends on several relevant components of the problem as the policy question to be addressed and the availability and quality of the data.

The viewpoint of experts either researchers or institutions is that uncertainty does affect several steps of microsimulation exercises. For instance, an extreme event or a policy could affect socioeconomic trends (see Rozenberg and Hallegate, 2016, for an example of microsimulation on Vietnamese households). In this case, both Hallegatte et al., (2011) and Rozenberg and Hallegate, (2016) they acknowledge that "assessing the impact of climate change on poverty is a daunting task, since some changes arising because of climate change will determine the future impacts of climate change on poor people and on poverty rates as much as climate change itself". For instance, poor people living in rural areas will migrate or jobs in some sector will disappear. Then, there is going to provoke shocks in places, sectors or ecosystems affecting the most people living in those areas. In the context of our simulations, the effects are going to translate from income or price shocks to demand, but there are many other variables that can be affected and even CGE or IAM models cannot consider given those uncertainties. In economic terms, we can establish at the end of the day distributive or poverty measures, but they are not going to capture all possible effects or even they are going to capture some effects with a lot of uncertainty. The solution to these challenges of microsimulation modelling is usually to increase the model scope trying to improve the ranges of impacts captured by the proposed tool.

Finally, the dynamic nature of a tool obtained by including behavioural responses could not be complete when the simulation horizon is long since the responses will require another dynamic aspect to be collected both in the specification of the underlying model as well as in the projections of the inputs composing the microsimulation tool. We must bear in mind that some economic and sociodemographic variables are going to be time-varying, and it requires as well to update the data (the population) behind the model. This last issue is always a challenge in microsimulation models involving research questions related to pension systems (see, for instance, Dekker et al., 2010).

Conclusions

This report has presented the functioning of the microsimulation tool developed as part of the CHIPS project. We describe an illustration for Mexico of the effects on households of a carbon tax on energy products, which tries to achieve reductions in CO_2 emissions associated with domestic energy consumption. Apart from microdata, we first need the parameters of a demand system. We estimate a complete demand system using Mexican household data, then we use the parameter estimates to simulate the revenue and distributional effects of the application of a carbon tax with in two scenarios $25 and $50/tCO2. Then, we propose to use the additional revenue generated to compensate households for the negative impacts of the reform.

The results show that the reforms considered would reduce energy consumption and associated emissions, and would also have a progressive impact on welfare, affecting richer households more, because of the progressive effect of the gasoline tax, which offsets the regressive impact of the electricity tax. In any case, the reforms, by increasing the energy expenditure of poor households, would increase poverty and inequality in Mexico. The use of the revenue generated through lump-sum transfers, especially if these are targeted to the poorest households, would reduce inequality and poverty relative to the baseline situation without reform, making the reforms with compensatory packages have a net progressive distributional impact.

Therefore, the implementation of a carbon tax on energy goods with properly defined compensation schemes would achieve reductions in energy consumption and associated CO2 emissions of households, contributing to meet the Mexican commitments derived from the Paris agreement, while at the same time reducing inequality and poverty.

References

Banks. J., R. Blundell and A. Lewbel (1997), "Tax reform and welfare measurement: Do we need demand system estimation?", *The Economic Journal* 106, 1227-1241.

Banks. J., R. Blundell and A. Lewbel (1997), "Quadratic Engel curves and consumer demand", *Review of Economics and Statistics* 79, 527-539.

CRE (Comisión Reguladora de Energía) (2019), *Factor de emisión del sistema eléctrico nacional*.

De Agostini. P., J. Hills and H. Sutherland (2018), "Were we really all in it together? The distributional effects of the 2010–15 UK coalition government's tax-benefit policy changes", *Social Policy Administration* 52, 929-949.

Deaton, A. and J. Muellbauer (1980). "An almost ideal demand system", *American Economic Review* 70, 312-326.

Dekkers, G., H. Buslei, M. Cozzolino, R. Desmet, J. Geyer, D. Hofmann, M. Raitano, V. Steiner, P. Tanda, S. Tedeschi, and F. Verschueren (2010). The flip side of the coin: The consequences of the European budgetary projections on the adequacy of social security pensions. *European Journal of Social Security 12*(2), 94–121.

Fankhauser, S. (1994), "The social costs of greenhouse gas emissions: an expected value approach", *Energy Journal* 15, 157-184.

Harding, A. (1996), "Introduction and overview", in A. Harding (ed.), *Microsimulation and Public Policy*, Number 232 in Contributions to Economic Analysis, Chapter 1, 1-22. Amsterdam: North-Holland, Elsevier.

Harding, A. and A. Zaidi (2010), *New Frontiers in Microsimulation Modelling*, Routledge, London.

Heckman, J. J., I. Ichimura and P. E. Todd (1997), "Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme", *Review of Economic Studies* 64, 605-654.

Heindl, P. (2015), "Measuring fuel poverty: general considerations and application to German household data", *FinanzArchiv* 71, 178-215.

INECC (2014), Factores de emisión para los diferentes tipos de combustibles fósiles y alternativos que se consumen en México. Tercer Informe. Informe Final. Instituto Nacional de Ecología y Cambio Climático, Mexico, DF.

IEA (2019), CO_2 emissions from fuel combustion. OECD/IEA, Paris.

INEGI (2022a). *Encuesta nacional de ingresos y gastos de los hogares (ENIGH)*.

INEGI (2022b). *Índice nacional de precios al consumidor*.

King, M. A. (1983), “Welfare analysis of tax reforms using household data”, *Journal of Public Economics* 21, 183-214.

Labandeira, X., J. M. Labeaga and M. Rodríguez (2006), “A residential energy demand system for Spain”, *The Energy Journal* 27, 87-112.

Labandeira, X., J. M. Labeaga, X. López-Otero and T. Sterner (2022), “Distributional impacts of carbon taxation in Mexico”, *Cuadernos de ICE* 104, 111-141.

Li, J. and C. O’Donoghoue (2013), “A methodological survey of dynamic microsimulation models”, *International Journal of Microsimulation 6*, 3-55.

Lucas Jr, R. E. (1976), “Econometric policy evaluation: A critique”, *Carnegie-Rochester conference series on public policy*, Vol. 1. 19-46, North-Holland.

OECD. (2022). *Exchange rates*. Paris.

O’Donoghue, C. (2021), *Practical Microsimulation Modelling*, Oxford University Press, Oxford.

Orcutt, G. H. (1957), “A new type of socio-economic system”, *The Review of Economics and Statistics* 39, 116-123.

Orcutt, G. H. (1960), “Simulation of economic systems”, *American Economic Review* 50, 893-907.

Rozenberg, J. and S. Hallegate (2016), “Modelling the impacts of climate change on future Vietnamese households. A micro-simulation approach”, WP 7766, The World Bank.

Spadaro, A. (2007), *Microsimulation as a Tool for the Evaluation of Public Policies: Methods and Applications*, Fundación BBVA, Madrid.

Reynolds, M. and E. Smolensky (1977), *Public expenditure, taxes and the distribution of income. The United States 1950, 1961, 1970*. Academic Press, New York.

SENER (Secretaría de Energía) (2019), *Balance nacional de energía 2018*. Secretaría de Energía.

Thomas, A. (2022), “Who would win from a multi-rate GST in New Zealand: evidence from a QUAIDS model”, *New Zealand Economic Papers* 56, 1-28.

Table 1. Summary statistics (shares, w, and prices, p)

ENIGH Mexico (2006-2018)					
	N	Mean	SD	p10	p90
w1	230295	.399	.185	.156	.647
w2	230295	.006	.030	.000	.000
w3	230295	.057	.059	.000	.134
w4	230295	.109	.102	.013	.243
w5	230295	.066	.054	.020	.127
w6	230295	.025	.062	.000	.066
w7	230295	.095	.117	.000	.246
w8	230295	.042	.046	.000	.098
w9	230295	.030	.053	.000	.085
w10	230295	.019	.053	.000	.064
w11	230295	.059	.098	.000	.189
w12	230295	.093	.074	.030	.172
p1	230278	83.407	16.686	57.890	10.303
p2	21412	78.980	20.836	45.737	100.150
p3	184339	89.832	9.752	75.345	100.814
p4	226426	98.840	12.136	78.706	112.395
p5	227232	86.200	13.649	62.706	100.226
p6	125429	82.503	15.186	59.688	99.419
p7	150027	73.856	18.507	48.735	98.809
p8	230295	88.414	9.528	75.113	98.900
p9	230295	86.299	11.850	75.386	99.790
p10	60299	80.604	15.170	58.712	99.514
p11	230295	82.913	15.586	60.977	99.669
p12	227754	86.144	12.131	68.449	99.888

Notes.

1. Shares and prices of the 12 COICOP goods are the following:

w1, p1: share in food and non-alcoholic drinks
w2, p2: share in alcoholic drinks and tobacco
w3, p3: share in clothing and footwear
w4, p4: share in housing expenditures -including fuel for housing and water
w5, p5: share in durables for housing
w6, p6: share in health
w7, p7: share in transport
w8, p8: share in communications
w9, p9: share in leisure
w10, p10: share in education
w11, p11: share in hotels, food and drinks out of home
w12, p12: share in other non-durable goods

2. We consider all available households even if they do not consume the corresponding good.

Acknowledgement

The project CHIPS is part of AXIS, an ERA-NET initiated by JPI Climate, and funded by FORMAS (SE), DLR/BMBF (DE, Grant No. 01LS1904A), AEI (ES) and ANR (FR) with co-funding by the European Union (Grant No. 776608).