



How to Assess Poverty Reduction Policies in Portugal?

A Revision of Data and Methods

PROSPER

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1 Introduction

In Portugal, the percentage of the population living precariously has consistently remained high over the years: the material deprivation rate already exceeded 15% prior the Covid-19 pandemic, being above the European Union average of 12%. In 2020, this value increased by approximately 2 percentage points, representing an additional 200,000 people living under such conditions. Furthermore, the high poverty rate in Portugal is a particularly concerning situation since this phenomenon does not seem to be transitory: 72% of the population living in poverty in 2018 was poor in at least two of the three previous years.

Besides being a reflection of fragile economic growth and income stagnation, these values are symptoms of some degree of insufficiency on the side of public policies to reduce poverty. Understanding exactly to what extent (and through what mechanisms) public policies are able to act on this phenomenon is crucial to guarantee that the resources used in them are effectively well allocated and that there is a continuous improvement in the process of their design and execution.

Measuring concretely how each policy, and the combination of different policies, has an impact at an individual and aggregate level implies studying its social impact and considering metrics which consider quality over quantity: for example, a vocational training program can certify 100 workers, while still not leading to any improvement in the employment prospects of these individuals, or failing to guarantee long-term effects. However, in Portugal, there is no consistent methodology for evaluating public policies that focuses on results that are really relevant, not only in the short term, but also in the long term. This dynamic dimension is especially important given the persistent nature of poverty, its social dimension, and the way in which it undermines cohesion and sustainable economic growth.

Naturally, it is never possible to say with certainty and in advance what the effects of a policy will be. Ideas that sound good in theory can disappoint in practice, whereas others turn out to be unexpectedly successful. Even policies that have been tried in the past can have different effects than before when seemingly unrelated circumstances have changed in the meantime. In general, modern poverty reduction policies have such complex effects and are so strongly interdependent that *a priori* their exact consequences can never be predicted. Indeed, without systematic monitoring and evaluation, it is almost impossible to separate policies that work well from those that do not. Counterfactual impact evaluation constitutes therefore the cornerstone of evaluation efforts in the field of poverty reduction programmes. This is based on the need to collect evidence and determine whether policy objectives have been met and, ultimately, whether the resources were used efficiently. These answers feed back into the design and implementation of future interventions and budgetary decisions.

Counterfactual impact evaluation is fundamentally a method of comparison which involves comparing the outcomes of interest of those having benefitted from a policy or programme (the “treated group”) against those of a group similar in all respects to the treatment group (the “comparison/control group”), the only difference being that the comparison/control group has not been exposed to the policy or programme. The comparison group provides information on “what would have happened to the members subject to the intervention had they not been exposed to it”, the counterfactual case. There are several rigorous methods which allow to perform this type of analysis, such as: difference in difference approach; propensity score matching; regression discontinuity; or instrumental variables (IV). The World Bank’s guide on Impact Evaluation¹ (Chapters 3 to 8) is a useful tool, providing extensive information on how to perform these analyses.

Furthermore, while experimental and quasi-experimental evaluation designs can be quite powerful, there are several shortcomings associated with these designs, particularly in terms of practicality. To address these, it’s important to approach evaluation efforts through a theory-based perspective. This is usually based on an explicit theory of change or logic model that explains the theory of a development intervention. The evaluation is then designed to test the theory to see if it holds true.

So even though there are numerous innovative tools and methods to assess policies rigorously, these contrast with the methodologies still used in the public sector to evaluate projects and measure results. It is necessary to close the gap that still exists between the academic environment, where paradigms are constantly changing, and the public sector, where an approach based on expenditure measurement and quantitative metrics is perpetuated. In this sense, it is proposed to review innovative experimental methods that can be applied in the evaluation of public policies for poverty reduction.

Naturally, the adoption of these methodologies largely depends on the existence of complete and quality information. It happens to be the case that the Portuguese information and statistics system is one of the best in the world, comprising relevant and extensive data that, when well processed and articulated, is capable of revolutionizing the way in which public policies are carried out and the way results are monitored and measured. Overlooking this information implies missing the opportunity to fully understand the impact of each project and the mechanisms that explain its success or failure.

This project consists of an extensive review and evaluation of the existing databases in Portugal, and potential aspects to enhance them. We do so with a special focus on the assessment of poverty reduction policies, which largely benefit from a mix of different sources of information

¹Gertler, P., Martinez, S., Premand, P., Rawlings, L., Vermeersch, C. (2016). *Impact Evaluation in Practice*. Second Edition. Inter-American Development Bank and World Bank.

in order to expand their reach. The outline of this paper is as follows: Section 2 discusses the most recent and innovative approaches in the literature of poverty measurement, which further consolidate its multidimensional nature. Section 3 provides an overview of the existing databases in Portugal, including details on data processing and variables which enable policy assessment. Section 4 describes some suggestions on how to leverage Portuguese data to fit the poverty analyses explored in Section 2. Finally, section 5 concludes.

2 Poverty Measurement

The traditional measurement of poverty focuses on income or expenditure based on a minimum threshold required to purchase a basket of essential goods and services. People whose income falls under the set threshold are considered poor.

The most widely known indicators developed under this framework are the Foster-Greer-Thorbecke (FGT) indices, described by:

$$FGT_{\alpha} = \sum_{i=1}^H \left(\frac{z - y_i}{z} \right)^{\alpha}$$

- **Relative poverty rate** or **Headcount ratio**: $\alpha = 0$

This represents the fraction of the population that lives below the poverty line.

- **Poverty gap index** (intensity): $\alpha = 1$

This represents the average poverty gap in the population, as a proportion of the poverty line.

- **Squared poverty gap index** (severity): $\alpha = 2$

This index averages the squares of the poverty gaps relative to the poverty line. Extreme poverty is given greater weight than less poverty. While the two reduced indexes are widely used, the most common FGT-specific index in development economics is the $\alpha = 2$ version, which is the lowest (whole) parameter to weigh income inequality along with poverty.

Other important definitions include:

- **Absolute poverty line**

Defined by the World Bank as \$2.15 using 2017 prices. This means that anyone living on less than \$2.15 a day is considered to be living in extreme poverty.

- **Relative poverty line**

This poverty line changes from country to country. OECD considers the threshold for relative poverty to be 50% of a country's median equivalised disposable income after social transfers². Eurostat uses the same definition with 60%.

However, vital aspects of well-being might not be fully captured through monetary measures alone. To address this shortcoming, Multidimensional Poverty Measures have been adopted as

²The equivalised disposable income is the total income of a household, after tax and other deductions, that is available for spending or saving, divided by the number of household members converted into equalised adults; household members are equalised or made equivalent by weighting each according to their age

an official indicator for the *United Nations 2030 Agenda* and its Sustainable Development Goals (SDGs) as “SDG 1.2.2: Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions”.

Indeed, it was shown that over a third of those experiencing multidimensional poverty are not captured by the monetary headcount ratio, which suggests that a country’s MPM is at least as high as or higher than monetary poverty.³ Taking into account the additional role of nonmonetary dimensions to poverty and their importance to general well-being, the MPM can present the extent to which these deprivations arise and overlap. Therefore, MPM is a useful tool to identify the most vulnerable people – the poorest among the poor, revealing poverty patterns within countries and over time, enabling policy makers to target resources and design policies more effectively.

Given the relevance and recent emphasis on multidimensional poverty, we have chosen some indicators, developed by prominent economists, which employ cutting edge techniques and contribute to further enhance rigorous poverty measurement, crucial for policy design and evaluation.

2.1 Akire-Foster Method and Applications

The Alkire-Foster (AF) is a widely-used flexible methodology for measuring multidimensional poverty which is capable of accommodating different indicators, weights and cut-offs. It involves counting the different types of deprivation that individuals experience at the same time, such as a lack of education or employment, or poor health or living standards. These deprivation profiles are analysed to identify who is poor, and then used to construct a multidimensional poverty index (MPI).

To identify the poor, the AF method counts the overlapping or simultaneous deprivations that a person or household experiences in different indicators of poverty. The indicators may be equally weighted or take different weights. People are identified as multidimensionally poor if the weighted sum of their deprivations is greater than or equal to a poverty threshold – such as 20%, 30% or 50% of all deprivations.

The most common way of measuring poverty is to calculate the percentage of the population who are poor, that is, the headcount ratio (H). Having identified who is poor, the AF methodology generates a unique class of poverty measures ($M\alpha$) that goes beyond the simple headcount ratio. Three measures in this class are of high importance:

- Adjusted headcount ratio ($M0$), otherwise known as the MPI: This measure reflects both

³World Bank. (2020). *Poverty and Shared Prosperity 2020:Reversals of Fortune*. Washington, DC. <https://openknowledge.worldbank.org/handle/10986/34496>

the incidence of poverty (the percentage of the population who are poor) and the intensity of poverty (the percentage of deprivations suffered by each person or household on average). M0 is calculated by multiplying the incidence (H) by the intensity (A).

- Adjusted Poverty Gap (M1): This measure reflects the incidence, intensity and depth of poverty. The depth of poverty is the average ‘gap’ (G) between the level of deprivation poor people experience and the poverty cut-off line.
- Adjusted Squared Poverty Gap (M2): This measure reflects the incidence, intensity, and depth of poverty, as well as inequality among the poor (captured by the squared gap, S).

The AF Method is unique in that, by measuring intensity, it can distinguish between, for instance, a group of poor people who suffer two deprivations on average and a group of poor people who suffer five deprivations on average at the same time. This method can be used to target people who are deprived in multiple ways for services or conditional cash transfers, and can also be used to monitor the effectiveness of programmes over time.

In 2014, Alkire et al. developed a set of experimental indices of multidimensional poverty, using cross-sectional EU-SILC data. The indices employ the Alkire-Foster methodology and draw on existing EU-2020 indicators, as well as on indicators of health, education and the living environment. With this, the authors develop three experimental indices of multidimensional poverty, using individual adults (+16 years old) as unit of analysis. Household level variables are used to identify individuals as deprived or non-deprived in terms of at risk of income poverty, severe material deprivations, (quasi) joblessness, housing, noise, crime and pollution.

The three experimental indices presented in this paper each have four or five dimensions. The authors consider “dimensions” as organising concepts which govern the weights attached to the indicators, or which are used to communicate the results to the general public. Naturally, the discussion of the appropriate dimensions to organise the measurement of deprivation has a long history, which can inform present discussions.

The first two measures have four dimensions each. Three out of these four – living standards as measured by EU-2020 poverty indicators, health, and education – are present in nearly every treatment of poverty. Drawing on the arguments provided in Whelan et al. (2014) and Guio and Maquet (2006), the authors add to these a dimension of the living environment, which include the roof and neighbourhood considerations: noise, pollution and safety. Finally, measure 3 includes these but separates out the ‘Material Deprivation’ dimension of the EU-2020 poverty index into a separate dimension, leaving work intensity and income together in a separate dimension. Therefore, each measure conveys different information on the poverty status of the population, which allows for a comprehensive analysis into the composition of poverty.

In sum, the three indices include information on 12 indicators, which range from income poverty to severe material deprivation, joblessness, health and living environment.

Measure 1

In Measure 1, the 12 indicators are organized into four dimensions - EU2020, Education, Environment and Health. Each dimension is equally weighted, and each indicator within a dimension is equally weighted.

Measure 2

Measure 2 replicates Measure 1 except that the indicator of material deprivation is considered as a fifth dimension.

Measure 3

Measure 3 organises the 12 indicators into six dimensions by breaking up (and effectively trebling the weight on) the EU-2020 indicators, which are each considered separate dimensions. In Measure 3, the weight on AROP, (quasi)joblessness and severe material deprivation are 1/6 each, as are the weights on health, education and environment.

Figure 1 below provides a schematic visualization of the 3 proposed measures.

<i>Dimension</i>	<i>Variable</i>	<i>Respondent is not deprived if:</i>	<i>M1</i>	<i>M2</i>	<i>M3</i>
EU 2020	AROP	The respondent's equivalized disposable income is above 60 per cent of the national median	1/12	1/10	1/6
	Quasi-Joblessness	The respondent lives in household where the ratio of the total number of months that all - household members aged 16-59 have worked during the income reference year and the total number of months the same household members theoretically could have worked in the same period is higher than 0.2	1/12	1/10	1/6
	Severe material deprivation	The respondent has at least six of the following: the ability to make ends meet; to afford one week of holidays; a meal with meat, chicken, fish or vegi equivalent; to face unexpected expenses; and, to keep home adequately warm. Or the respondent has a car, a colour TV, a washing machine, and a telephone.	1/12	1/5	1/6
Education	Education	The respondent has completed primary education	1/4	1/5	1/6
Environment	Noise	The respondent lives in a household with low noise from neighbourhood or from the street	1/16	1/20	1/24
	Pollution	The respondent lives in a household with low pollution, grime or other environmental problems	1/16	1/20	1/24
	Crime	The respondent lives in a household with low crime, violence or vandalism in the area	1/16	1/20	1/24
	Housing	The respondent lives in a household with no leaking roof, damp walls, rot in window frames of floor	1/16	1/20	1/24
Health	Health	The respondent considers her own health as fair or above	1/16	1/20	1/24
	Chronic Illness	The respondent has no chronic illness or long-term condition	1/16	1/20	1/24
	Morbidity	The respondent has no limitations due to health problems	1/16	1/20	1/24
	Unmet Med. Needs	The respondent does not report unmet medical needs	1/16	1/20	1/24

Figure 1: Multidimensional Poverty Indices

For each measure, the authors provide results for (raw) headcount and intensity ratios.

Since the composition of poverty is affected both by the rates of deprivations in each indicator and also by the weights applied to it, it can also be useful to perceive the levels of deprivation in each indicator individually, separately from the weights. To do this, the authors construct a “censored” headcount ratio, which shows the percentage of people who are identified as poor and are deprived in each particular indicator⁴. Furthermore, the deprivations with the highest weight (income, labor, education) have relatively less differences between raw and censored headcounts than the others because one requires fewer additional indicators to be identified as poor. Of these three, the differences between raw and censored headcounts in income tend to be larger, but this is not a fixed rule.

Results

The levels of poverty provided by Measure 1 tend to be the highest, followed by Measure 2 and 3.

In Measure 1, the relative contribution of labour and material deprivation declines as overall poverty in a country increases, as do the relative contributions of the health variables. The educational deprivations’ contribution to multidimensional poverty increases strikingly in the poorer countries. In Measure 3, there is a similar although less marked trend. Material deprivation is a crucial component across all countries.

The authors then use 2009 EU-SILC data to analyse poverty levels in some countries. For Portugal, deprivations with the highest weight - at-risk-of-poverty rate, (quasi) joblessness and severe material deprivation (regarding income and labour) have relatively less differences between raw and censored headcounts than the others because one requires fewer additional indicators to be identified as poor: 15.4% of the population is income poor and only 12.1% is both income deprived and poor. It is clearly shown, therefore, that by using income only as a poverty measure, 3.2% of the population would be misidentified as poor since none of them is deprived in any other dimension. Contrastingly, the gap between raw and censored headcount ratios is largest for chronic illness, crime, noise and education. This implies that many people are deprived in these areas, although not significantly deprived in other areas to be considered poor.

2.2 Commitment to Equity (CEQ) Methodology

The Commitment to Equity (CEQ) Institute works to reduce inequality and poverty through comprehensive and rigorous tax and benefit incidence analysis, and active engagement with the policy community. Tax and benefit incidence studies using the CEQ methodology have been

⁴Note: Censored headcount ratios are \leq than the uncensored/raw. The difference shows whether some persons who are deprived in that indicator are not simultaneously deprived in enough other indicators to be identified as multidimensionally poor. In this way the poverty cutoff may be used to ‘clean’ the observations of deprivations that do not signify poverty.

completed in a wide array of countries in all regions of the world, and have been published in leading peer-reviewed journals.

Even though Portugal has not been subject to this type of analysis, one could consider the example of Spain instead, where Bengoechea and Quan (2020) apply the CEQ methodology to assess the effects of government taxation and public spending on income distribution, inequality and poverty.

Fiscal Incidence Analysis and the CEQ Method (Lustig, 2019)

Income and wealth inequality among and within countries is pervasive. Unequal opportunities translate into earnings inequality and concentration of power and wealth into unfair social contracts. Societies have two main ways to tackle this: first, by expanding poor people’s access to assets (especially through human capital) and bargaining power to level the playing field; second, by redistributing income through taxes and transfers. In both instances, the power of the state to redistribute assets, income, and wealth through fiscal policy plays a key role. In this context, fiscal incidence analysis is a crucial tool, which allows governments to assess how effective their current fiscal policies are in achieving their distributional objectives, promoting growth, expanding opportunities, and accelerating poverty reduction.

To assess whether the fiscal system decreases poverty, the CEQ method traces out the change in poverty across “income concepts”.

Using an accounting approach, where there are no behavioral responses, no general equilibrium effects and no dynamic effects associated with tax and transfers policy, counterfactual income in the presence of a tax(/transfer) is simply the pre-fiscal income minus(/plus) the tax(/transfer). Thus, the building block of fiscal incidence analysis is the construction of “income concepts.” That is, starting from a pre-fiscal income concept or market income (mainly, income from labour and capital and private transfers), each new income concept is constructed by adding the relevant transfers and subsidies and subtracting taxes to the previous income concept. A schematic presentation of this process can be seen in the figure below.

Fiscal incidence studies use microdata from household surveys combined with budget data from fiscal accounts and other administrative registries. The data requirements for a fiscal incidence analysis includes three main ingredients:

- A recent household survey (possible options: expenditure-income, consumption-based, expenditure, employment, Living Standard Measurement Surveys, etc) representative at the national level;
- A detailed description of the characteristics of each tax and spending item to be included in the analysis;
- Audited or confirmed budget and administrative data for the survey year, to provide the

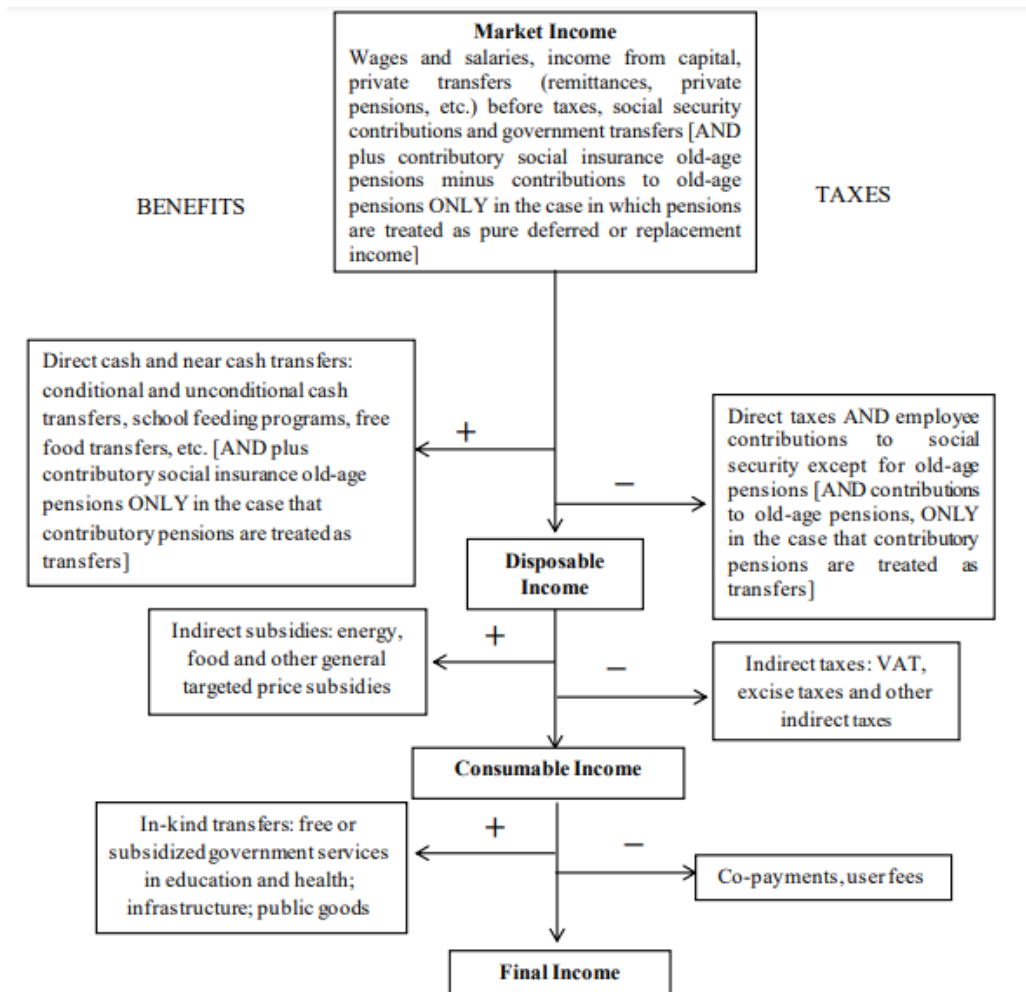


Figure 2: Income Concepts following an Accounting Approach to Fiscal Incidence (Source: Lustig and Higgins (2018), Figure 1-1.)

necessary details for allocating fiscal interventions.

Macroeconomic data can also be used as a third source of information to calibrate magnitudes of fiscal elements that are allocated across the individuals and households in the household survey.

Yet, some challenges arise due to the inconsistencies between information obtained from microdata such as household surveys and that found in macrodata such as government budgets, administrative registries (e.g., tax returns), and National Accounts. Two typical problems are, for instance, that the number of beneficiaries of a particular welfare program according to the household survey may differ substantially from the number recorded in administrative registries. A second and serious limitation of household survey data is the undercoverage and underreporting of top incomes. In part (but not only) due to the “missing rich” problem⁵, for most countries in the world, totals for household income and consumption from surveys do not match the equivalent totals from National Accounts.

To deal with this, the CEQ methodology uses the scale of the economy observed in the household surveys and scale-down administrative totals to keep proportions similar to those observed in National Accounts.

The poverty measures used are members of the Foster–Greer–Thorbecke (FGT) class of poverty measures and include the headcount index, poverty gap ratio, and the squared poverty gap ratio. This is done for a number of poverty lines, including commonly used “international poverty lines”, national extreme and moderate poverty lines, and any other extreme and moderate poverty line that is relevant, such as a relative poverty line set as a percent of median income (commonly 50 or 60 percent).

Poverty indicators are anonymous by definition. As a result, poverty comparisons are silent about whether pre-fiscal poor individuals were made poorer or non-poor individuals were made poor by the net effect of taxation and public spending. Even if a tax and transfer system unambiguously reduces poverty (and inequality), it has been shown that the system can make a portion of the poor poorer and some of the non-poor poor. To quantify this phenomenon one can use the newly developed indicator of fiscal impoverishment (Higgins and Lustig, 2016).

To study the social groups that are getting more benefited from the redistribution system, the method consists in comparing the share of total direct transfers received by each income group with the share of total direct taxes paid and with the relative size of each group considered. Finally, to assess whether fiscal interventions make the whole fiscal system more equal, the method consists of analysing marginal contributions, which are equivalent to calculate the

⁵Income data is usually top-coded, and even if not, it is largely biased due to sample selection - find more details on this problem and potential corrections in following sections.

difference in inequality without and with a specific tax or transfer, by taking disposable income as the relevant end income concept, first, and using consumable income, secondly.

Bengoechea and Quan (2020) - Application of CEQ Method in Spain

The main fiscal incidence analysis equation applied in the paper is in line with the definition developed under the accounting approach and the basis for the CEQ Method:

$$Y_h = I_h - \sum_i T_i S_{ih} + \sum_j B_j S_{jh}$$

Where:

Y_h = Income after taxes and transfers.

I_h = Income before taxes and transfers.

T_i = Taxes.

S_{ih} = Share of Tax i paid by unit h.

B_j = Transfers.

S_{jh} = Share of Transfer j received by unit h.

To gather all the information necessary for the construction of all the income concepts and fiscal interventions contained in the analysis, the authors use survey data/direct identification, imputation/inference from the available data or the complete simulation of the interventions.

Direct Identification refers to data directly obtained from the main reference survey. In some cases, it might be possible to infer which families or individuals were affected by a policy or intervention based on whether the value they report in that specific question matches a possible value of the intervention. The imputation method uses information that directly identifies beneficiaries or payers from the survey. Finally, a simulation is used when both the information on beneficiaries (taxpayers) and benefits received (taxes paid) is absent from the survey, one can estimate the latter based on the program (tax) rules. Lustig (2016) provides further details on this procedure.

Figure 3 provides an overview of the estimation strategy employed for each component of the disposable income indicator.

The construction of the CEQ core income concepts require the combined use of data from surveys (in this particular paper, three: “Encuesta de Condiciones de Vida” (ECV - Spanish Living Conditions Survey, equivalent to the Portuguese ICOR); “Encuesta de Presupuestos Familiares” (EPF) for the simulation of indirect taxes; and “Encuesta Nacional de Salud” for health care in-kind transfers) together with the fiscal-administrative data.

Results

Estimation Strategy	
A. Transfers	
A.1. Contributory Pensions	Inference + Simulation
A.2. Direct cash transfers	
+ Non-contributory pensions	Imputation + Direct Identification
+ Unemployment benefits	Direct Identification
+ National family transfers	Imputation + Direct Identification
+ Regional family transfers	Imputation + Direct Identification
+ MIG	Imputation + Direct Identification
A.3. Indirect subsidies	
+ Food	Imputation + Simulation
A.4. In kind transfers	
+ Education	Imputation + Simulation
+ Health	Imputation + Simulation
B. Taxes	
B.1. Contributions to Pensions	Inference + Simulation
B.2. Direct Taxes	
- Personal Income Tax (IRPF)	Imputation + Direct Identification
- Other contributions to social security	Inference + Survey Data
- Property Tax	Direct Identification
B.3. Indirect Taxes	
- Value Added Tax	Inference + Simulation
B.4. Co-payments	

Figure 3: Estimation Strategy employed by Bengoechea and Quan (2020)

Applying the CEQ framework allows for interesting conclusions: the authors verify that the Spanish redistribution structure works efficiently in reducing inequality and poverty. The results suggest, however, that it is not totally progressive and that the different fiscal interventions could be better designed. Especially given the different structure that each fiscal system has in regions with high income inequality.

Results also show how the moderate poor are the most benefited individuals from fiscal interventions. Their income levels grow much faster than the other two groups considered (ultra poor and extreme poor) as income moves from market income plus pensions to final income.

2.3 Survey Correction Method by Blanchet et al.(2022)

Household surveys have been an invaluable tool for tracking the evolution of society. But in recent years, the research community has grown increasingly concerned with their limitations. In particular, and as highlighted in the CEQ Methodology section, surveys have struggled to keep track of the evolution of the top tail of the distribution, due mainly to heterogeneous response rates, misreporting and small sample bias, which distort all sorts of distributional estimates. These biases end up affecting the way public policy is designed and evaluated. For this reason, researchers have been increasingly exploring a different source to study inequality: tax data. Yet, to date there is no consensus on how to best reconcile both sources of information, given the multiple biases at play.

The paper by Blanchet, Flores and Morgan (2022) proposes a novel method rooted in standard calibration theory, to directly confront the problem of survey non-response between survey micro-data and anonymous tax data. The result of this calibration-inspired approach should be a more representative dataset that can serve as a basis to study the different dimensions of social inequality. The algorithm is built in such way that it automatically generates, from

raw surveys and tax data, an adjusted micro-dataset including new modified weights and new observations, while preserving the consistency of other pre-existing sociodemographic variables, at both the individual and aggregate level.

Intuition

The fundamental aspect behind this approach lies in the fact that, intuitively, if some people are underrepresented in a survey, then mechanically others have to be overrepresented, since the sum of weights must ultimately equal to the population size. Thus, any modification of one part of the distribution is bound to have repercussions on the rest. In particular, it makes little sense to assume that the survey is not representative of the rich, and at the same time that it is representative of the non-rich.

In the figure below we find a representation of a “true” and biased income distribution. The solid blue line represents the survey density f_X . The dashed red line represents the tax data density f_Y , which is only observed at the top. For high incomes, the survey density is lower than the tax data density, which means that high incomes are underrepresented. If some individuals are underrepresented, then other have to be overrepresented: they correspond to people below the point y^* .

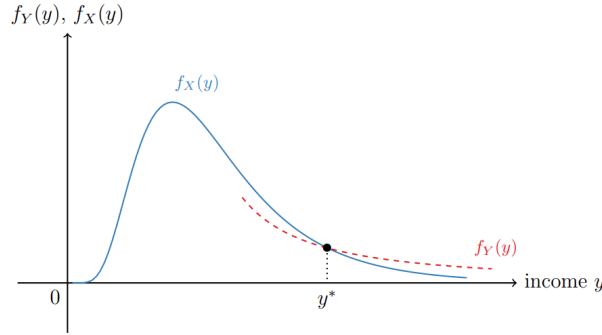


Figure 4: A «true» and biased income distribution. (Source: Blanchet et al., 2022)

Considering that $\theta(y) = f_X(y)/f_Y(y)$ is the ratio of the survey density to the true density at the income level y , the authors argue that the appropriate correction procedure here would be to increase the value of the density above it, and decrease its value below it. The intuition behind reweighting is that it is necessary to multiply the survey density f_X by a factor to make it equal to the true density f_Y . In practice, this means multiplying the weight of any observation Y_i by $1/\theta(y)$. This is seen graphically in Figure 5 below:

The solid blue line represents again the survey density f_X and the dashed red line represents the tax data density f_Y . Above the merging point \bar{y} , the reweighted survey data have the same distribution as the tax data (dashed red line). Below the merging point, the density has been uniformly lowered so that it still integrates to one, creating the dotted blue line. The *merging*

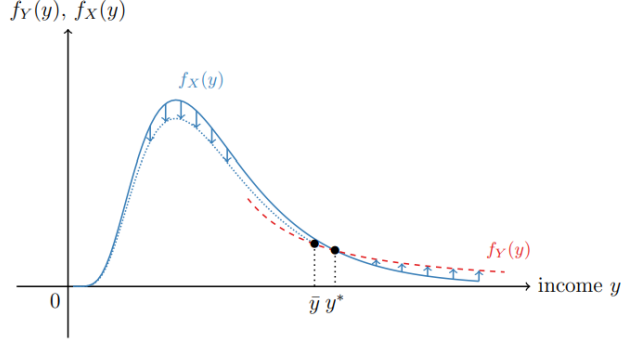


Figure 5: The intuition behind the reweighting step. (Source: Blanchet et al., 2022).

point, \bar{y} , is the value at which the procedure merges observations from the tax data into the survey.

With this in mind, the method can be described in three steps: first is the choice of the merging point, second is the reweighting step, and third is the replacing step.

Merging Point

The main innovation of this approach resides in the endogenous determination of a “merging point” — the point at which tax and survey information are joined. The choice of merging point emerges as the result simple and data-driven procedure:

Assuming that the bias function $\theta(y)$ follows the form:

$$\theta(y) = \begin{cases} \bar{\theta} & y < \bar{y} \\ f_X(y)/f_Y(y) & y \geq \bar{y} \end{cases}$$

The cumulative bias function is defined as: $\Theta(y) = \frac{F_X(y)}{F_Y(y)}$

The merging point \bar{y} should be the highest value y such that $\Theta(y) = \theta(y)$, as illustrated in Figure 6 below.

Reweighting

The purpose of this step is to reweight survey observations using tools from standard survey calibration theory. It allows to match the survey data to a histogram approximation of the tax data density, while ensuring the representativeness of the survey in terms of other sociodemographic variables such as gender, age, household type, etc.

The calibration procedure is quite complex, especially given the fact that survey representativeness in other variables beside income must remain intact. With this in mind, the authors describe the application procedure as follows:

1. Discretize the distribution of the variable. This is because the calibration problem is

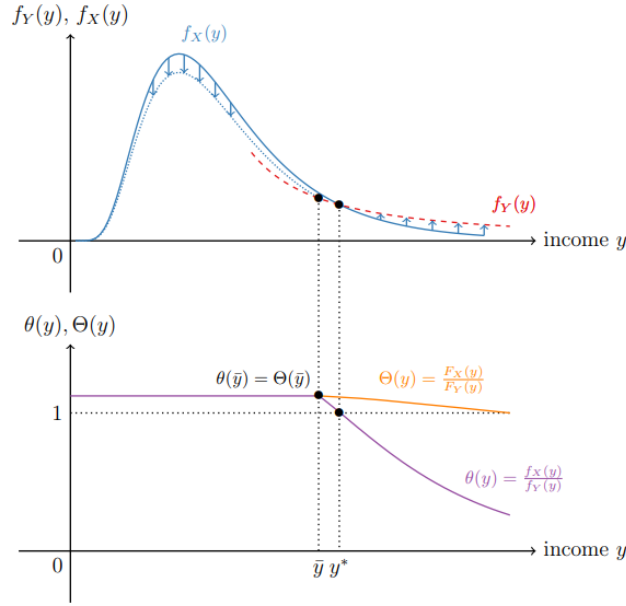


Figure 6: The choice of merging point (Source: Blanchet et al., 2022).

presented to enforce the aggregate value of variables. Thus, in order to use it to enforce the distribution of a variable, we have to discretize it⁶.

2. Obtain the distribution discretized over a narrow grid made up of all percentiles from 0% to 99%, 99.1% to 99.9%, 99.91% to 99.99% and 99.991% to 99.999%, while discarding tax brackets below the merging point.
3. Match the survey data to their corresponding tax bracket. It may be necessary to regroup certain tax brackets to make sure that we have at least one (and preferably more) observations in each bracket. The authors automatically regroup brackets to have a partition of the income distribution at the top such that each bracket has at least 5 survey observations.
4. Create dummy variables b_1, \dots, b_m for each income bracket. Assuming that the k -th bracket covers a fraction p_k of the population and that the sample-size is n , then the calibrated weights should satisfy:

$$\forall k \in \{1, \dots, m\} \quad \sum_{i=1}^n w_i b_{ik} = N p_k$$

Figure 7: Calibrated weights

⁶In the case of income tax data, the income distribution can be presented in various tabulated forms. To turn it into a continuous distribution one can apply the generalized Pareto interpolation method of Blanchet, Fournier, and Piketty (2017)

In practice, this enforces the income distribution through a histogram approximation of it.

5. For all the observations below the merging point, the dummy variables b_1, \dots, b_m are all equal to zero, so the weight adjustment only depends on a constant and possibly other calibration variables such as age and gender, but not income. This procedure, by construction, avoids distorting the bottom of the distribution because it is not necessary to enforce the constraints of the calibration problem.

Replacing

Lastly, the third step consists in replacing survey observations beyond the merging point with synthetic observations that exactly reproduce the distribution of income observed in the tax data, while keeping the distribution of covariates and their dependency with income according to the survey intact. In doing so, it is possible to get rid of the small-sample issues that prevent surveys from accurately describing the top tail of income distributions, retaining as much information as we can from the initial data.

This step is essential, given that the number of observations in the survey is still significantly lower than what would in theory be possible from administrative microdata. Thus, problems may arise in indicators of inequality. The combination of a low number of observations with fat-tailed distributions can create small sample biases for the quantiles and top shares (Okolewski and Rychlik, 2001; Taleb and Douady, 2015), and skewed distributions of the sample mean (Fleming, 2007). In most cases, this would lead to an underestimation of inequality levels.

To solve the case where tax statistics include a positive number of income-declarations beyond the survey's support, the authors inflate the number of data points in the survey by making k_i duplicates of each observation i . Then, they attribute to each new observation the weight $q_i = w_i/k_i$, where w_i is the calibrated weight from the previous step, $k_i = [\pi \tilde{w}_i]$ and $[x]$ is x rounded to the nearest integer. Therefore all new observations have an approximately equal weight close to $1/\pi$). The size of the new dataset, made out of the duplicated observations, can be made arbitrarily high by adjusting π .

If each observation is attributed the average income of their population share in the tax data, then by construction the income distribution of the newly created survey will be the same as in the tax data. The last step is to rank observations in increasing order by income to preserve the joint distribution between income and the covariates in the survey.

The previous two steps preserve the microdata structure of the original survey, making it possible to work with different statistical units, or equivalence scales, as one would do with regular survey data.

Results

The authors perform simulations that show that the method improves the quality of survey data, in that it reduces both the bias and the variance of inequality estimates. It also performs better than common alternative methods using the same data. By applying this approach to several countries, both developed and less developed, the paper shows that both levels and trends in inequality can be significantly revised.

3 Data Overview and Relevant Variables

3.1 Quadros de Pessoal (QP)

This data set is a Portuguese administrative linked employer-employee job title dataset. The entity responsible for this statistical operation with national scope is the *Gabinete de Estratégia e Planeamento* (GEP) from the Ministry of Employment, Solidarity and Social Security (MTSSS), making the data available for Statistics Portugal (*Instituto Nacional de Estatística*). The panel is obtained through an annual administrative census, where employers with at least one dependent worker are required to deliver (electronically or manually) to the responsible entity the information on their employees and their earnings (for example gender of worker, highest education level completed, job titles, collective bargaining agreement, date of birth, occupation, date of hiring, and so forth), as well as information on the firms (for example, sector of activity, and so forth) and establishments. This requirement is meant as a way to verify if firms are complying with labor law. Since the employer is the one actually reporting the data, variables such as worker qualifications are less prone to measurement errors than if they were self-reported. Data for Quadros de Pessoal has been collected since 1986, with interruptions in 1990 and 2001, and over time has suffered some adjustments in the data collected.

Some employers are exempted from reporting this information, though. Besides self-employed individuals, “central, regional and local administration and public institutes (for these entities only applicable to workers under individual employment contract) and employers of domestic service workers” are also exempted (*Quadros de Pessoal, Documento Metodológico*, page 1). Thus, QP covers virtually all firms and their dependent workers in Portuguese private sector. All the data refers to October and should be delivered in November every year. The unit of observation depends on the dataset. There is a worker, a firm and an establishment level dataset. Datasets of different years and units of observation are mergeable through the use of unique identifiers for workers, firms and establishment, respectively. The worker level dataset has around 3 million observations.

Regional Indicator Variable: To identify the firms’ and workers’ broad geographical regions, the dataset setup relies on the Nomenclature of Territorial Units for Statistics at the regional level (NUTS 2). According to this classification, firms can be located in Lisbon, in the North, in Alentejo, in the Center region, in Algarve, in Madeira, or in the Azores. There is also information for both NUTS 1 (a broader nomenclature, where the level of detail is coarser) and NUTS 3 (a more disaggregated nomenclature, with 25 sub-regions corresponding to intermunicipal communities).

Sector Indicator Variable: The data collected can be classified according to the sector in which the firms and workers operate. The categorization follows the *Classificação Portuguesa*

das Actividades Económicas Rev.3 (CAE Rev.3) and is divided into the following sectors: A) agriculture, animal production, hunting, forestry and fishing (sector eliminated in our paper), B) extractive industries, C) manufacturing industries, D) electricity, gas, steam, hot and cold water and cold air, E) water collection, treatment and distribution; sanitation, waste management and depollution, F) construction, G) wholesale and retail trade; repair of motor vehicles and motorcycles, H) transport and storage, I) accommodation, catering and similar, J) information and communication activities, K) financial and insurance activities, L) real estate activities, M) consulting, scientific, technical and similar activities, N) administrative and support service activities, O) public administration and defence; compulsory social security, P) Education, Q) human health and social support activities, R) artistic, entertainment, sports and recreational activities, S) other service activities and U) activities of international organizations and other extra-territorial institutions (section T does not appear in the data because Quadros de Pessoal excludes employers of domestic service workers and people producing for own consumption).

Education Variable: Quadros de Pessoal contains a information on the highest level educational attainment for each worker, reported by the employer in the following categories: “Inferior ao 1º ciclo do ensino básico”, “Ensino básico”, “Ensino secundário”, “Ensino pós secundário não superior nível IV”, “Curso técnico superior profissional”, “Bacharelato (BSc)”, “Licenciatura (BSc)”, “Mestrado (MA or MSc)” or “Doutoramento (PhD)”.

Income Variables: Employers report multiple information regarding the workers’ earnings, such as: base salary, supplemental compensation, total earned, normal monthly paid hours, supplemental monthly paid hours and normal weekly working period.

Several important and relevant studies have been conducted using this linked employer-employee data set. Namely, Portugal et al. (2018) assessed the evolution of the distribution of wages in Portugal from 1988 to 2013 using data from Quadros de Pessoal. The authors verify that during this period there was an overall growth in wages, and concluded that around three-quarters of this increase could be accounted by the rise of education levels.

Centeno and Novo (2014) also employed data of Quadros de Pessoal to look into the determinants of wage inequality. The authors observed that even though there was an increase in wage inequality during the period from 1984 to 2009, there was a drop in the rate at which inequality rose after the mid-90s. The slowdown in the upper-tail inequality can be accounted by an increase in the supply of skills. Indeed, the share of workers with a degree tripled during the 90s. At the lower-tail, wage inequality decreased, a result of the polarization of work (demand for low and high-skilled workers increased, while for intermediate-skilled workers decreased) and minimum wage increases.

3.2 Census Data

The Population and Housing Censuses – Census – are the largest statistical operations carried out in any country in the world and are designed to obtain information on the entire resident population, families and the housing stock. According to the United Nations (UN), Censuses are among the most complex and massive exercises that a nation undertakes. They require mapping the entire territory, mobilizing and training a large number of professionals, carrying out a vast public campaign, engaging the entire population, collecting individual information, compiling large amounts of information and analyzing and dissemination of a vast amount of data.

Censuses are part of a national statistical system, which may include other censuses (eg. agriculture), surveys, records and administrative files. They provide, at regular time intervals, typically every 10 years, the reference value of the population count, at national and local levels. For small geographic areas or subpopulations, they can be the only source of information for a wide range of demographic, socioeconomic and housing characteristics. The Censuses in Portugal are carried out by the National Institute of Statistics (Instituto Nacional de Estatística - INE), since 1940.

A 5% sample of the Census is available to the general public through the INE website, where we can find the results for the 1981, 1991, 2001 and 2011 (2021 should be available soon). This includes two sample tables: one for family and collective accommodation containing some variables of the building; and another for resident individuals, both with 5% of records and a common link variable for merging.

Incorporating Census data is crucial to study poverty since the vast indicators collected through this survey provide a unique setting to explore several dimensions of poverty (described in the sections below) contributing to a multifaceted and accurate analysis;

Given the extensive nature of the census, it collects many variables that can be key when assessing the living conditions of an individual. Among those, there are demographic ones (e.g., age, gender, marital status), geographic (e.g., current and past residence, whether an individual lived outside Portugal and when they arrived), socioeconomic (e.g., employment status, hours worked, job, sector, commuting time and mode of transportation), education (e.g., illiteracy, education level, university degree), housing (e.g., ownership, rent, number of residents, water supply, type of dwelling, heating, air conditioning, electricity, area, number of divisions, sewage, bathing facilities, accessibility, floor, roof), information about the family (e.g., number of dependent members, of people working), and also data regarding physical and mental disabilities. Classification by regional level (following NUTS 3) is also available. In 2011, the number of observations was around 10 million, which leaves the existing samples with about 500.000 observations.

3.3 Income Tax Data - IRS

Administrative tax data is crucial for many different reasons, which range from studying taxpayer behavior in response to tax policy reform to non-tax questions, for instance related to intergenerational mobility, firm production networks, or even poverty. Additionally, tax data can help prepare technical assistance and programmes, or monitor their implementation.

Tax data contains a wide variety of benefits. Unlike survey data, it is less prone to selective non-reporting at the top of the income distribution. And unlike census data, tax data contains more detailed information, and is collected at high frequency. Most types of tax data are now collected electronically, which minimizes errors. Furthermore, as the data is the product of actual economic processes, it measures variables with high precision, unlike survey data in which respondents provide ballpark figures as their response has no legal or fiscal consequences for themselves.

Administrative tax data for Portugal is available at the individual level through *Imposto sobre o Rendimento das Pessoas Singulares - Notas de liquidação* records. This data is available for the years 2014 and 2020 and includes variables on the global income declared, specific deductions, income deductions, recoverable losses, taxable income and net tax collection. It also includes information on the county and municipality corresponding to the fiscal address of the individual, and each year contains approximately 5 million observations. The individual ID is given by the NIF, the fiscal identifier. It is important to note that for the time being, this IRS data does not include any decomposition of global income into distinct components such as labor income, capital income, social security transfers, pensions, etc. Global income therefore includes:

- Income from dependent work
- Business and professional income
- Capital income
- Property income
- Equity increments
- Pensions

Nevertheless, such decomposition will be made available in the near future.

Using data from income tax is not uncommon to employ when studying poverty and inequality. Auten et al. (2013) looked into individual income tax return to understand if social mobility was related to income inequality. These authors concluded that regarding intergenerational mobility, approximately one third of the dependents from families that belonged to the lowest income quintile in 1987 were still in that same quintile 20 years later. As for long term mobility when comparing to peers, around half of the individuals that were in the lowest quintile remained there for the following 20 years.

3.4 Inquérito às Condições de Vida e Rendimento - ICOR (EU-SILC Living Conditions Survey)

The ICOR is an annual statistical survey carried out in Portugal since 2004, currently within the European framework, which establishes a common regime for European statistics concerning people and households, based on individual data collected from samples. The Commission Implementing Regulation specifies the technical aspects of organizing a sample survey in the field of income and conditions of life, applicable in all Member States, allowing the international comparison of national data.

This dataset provides rich and harmonized individual and household level information for income (e.g., wages, pensions, subsidies, contributions to social security) as well as social indicators such as labour (e.g., occupation, hours worked per week, years working, retirement age), education (e.g., school attendance, level of educational attainment, university degree, degree pre- or post-Bologna agreement, time to complete degree), health (e.g., receiving healthcare when needed, chronic illnesses, disabilities), housing conditions and the lived environment (e.g., ability to pay bills, eat healthy food, car ownership, whether children attend daycare or who they stay with, whether children attend compulsory schooling).

The detailed and rigorous collection of all the incomes of the selected households, by type and level of income, as well as the characteristics of each of its members, makes it possible to obtain statistical indicators on material and housing deprivation and on the distribution of income, poverty and social exclusion, being a crucial source of information for poverty measurement. The EU-2020 indicators of at-risk-of poverty rate, labor market outcomes, social exclusion and material deprivation are examples of indicators obtained with data from this survey.

The survey methodology ensures the monitoring of each family selected for the sample for four years in order to make possible studies on the impact of economic conditions and social policies on different social groups.

A new annual sample size of 19,320 accommodations was defined in 2018. For the years 2015-2017, the average number of accommodations observed is about 15 thousand.

Interesting studies that were performed with this type of data include Elstad (2016) analyzed EU-SILC surveys from 30 countries from 2008 to 2013 in order to understand the impact of the Great Recession in unmet need for medical care. The author observed that foregone medical care increased in most of the countries, and this effect was noticed the most in the countries where income inequality was higher.

Similarly, Maître et al. (2012) used data from EU-SILC for 14 countries to study the relation between low pay and household poverty and vulnerability. The probability of being low paid was related to gender, age, and also if the employee was the only earner in the household. Workers

that are low-paid face a higher poverty risk than those that are not, where poverty is rare.

Finally, Diogo (2018) in his paper “Child poverty and the social integration income in Portugal: the same problem, different trends” uses specifically ICOR data and finds that the proportion of children (0-17 years) among the recipients of Social Integration Income (RSI - *Rendimento Social de Inserção*) has been consistently declining for several years in contrast to a persistently high child poverty rate. This contradiction is demonstrated through the use of RSI data cross-referenced with INE statistics on child poverty (ICOR-EU-SILC), measured by monetary poverty. The author then puts forward some explanations behind this contradiction based on the legal transformations of the RSI and the difficulty of the state to develop measures of social support with impact on child poverty.

3.5 Base de População Residente (BPR)

The *Base de População Residente* is an harmonized database which incorporates Census data with information from several administrative sources - Instituto dos Registos e do Notariado, Serviço de Estrangeiros e Fronteiras, Instituto de Informática da Segurança Social, Gabinete de Estratégia e Planeamento do Ministério do Trabalho, Solidariedade e Segurança Social, Direção-Geral de Estatísticas da Educação e Ciência, Autoridade Tributária e Aduaneira, Caixa Geral de Aposentações, Instituto de Emprego e Formação Profissional, Direção-Geral de Proteção Social de Trabalhadores em Funções Públicas, Instituto do Emprego da Madeira, Secretaria da Educação Regional - Madeira and Direção Regional do Emprego e Qualificação Profissional dos Açores. It collects cross-sectional data annually, since 2014.

Since each individual does not carry an unique number identifier, matching information can be a challenge. There are three main identifying numbers (NIC, NIF and NISS), and each data source collects information on one, two, or all of them, which allows to match individuals across sources. Nevertheless, it is possible that for some observations no information about the identifier number was registered. In order to identify which individuals are residents, the construction of this dataset follows an approach based on “signs of life”, where it checks which datasets an individual appears in. After this process, it matches the information from all sources in order to characterize the individuals.

BPR has around 10 million observations but it is not guaranteed that for all of them there is data regarding all variables considered. Demographic variables, which are less than half of total variables, have total coverage (for example gender, age, marital status, residency). The coverage for the remaining variables, which tend to be work related (for example, sector, employment status, education) depends on whether it was possible to match the individuals between the different sources or not.

4 Leveraging Data for Poverty Analysis

In the previous sections, we have explored several innovative and comprehensive ways of measuring poverty, beyond the traditional methods, as well as the current state and scope of Portuguese data. Now, the aim of this section is to understand how the available databases could be leveraged to further enhance the measurement of poverty in our country, specifically to fit the poverty analyses detailed in Section 2.

4.1 Experimental Indices of Multidimensional Poverty, based on Alkire-Foster Method

To obtain the experimental indices developed by Alkire et al. (2014), survey data is the most adequate source, particularly the EU-SILC survey developed in Portugal, ICOR. Since the paper's indices were built using EU-SILC data, ICOR should be a perfect match in terms of variables, due to harmonized standards demanded for these surveys.

The authors already provide some guidelines for weights, indicators and cut-offs. It is important to note, however, that since these measures are experimental, the authors do not provide an extensive normative justification of the dimensions drawing on people's own values, the theoretical literature, the policy purpose of the measure, and other considerations. Such an extensive justification is provided in the case of official multidimensional poverty measures. For more information on dimensions and some indicators that have been used in the European context, Atkinson et al.(2002) is a good guide.

Employing this approach to more recent data would be an interesting exercise to examine the changes in multidimensional poverty dynamics in Portugal, including analysis of changes in overall poverty and in indicators. It would be particularly relevant to assess the changes over time of raw and censored headcount ratios (refer to Section 2.1 for more information on these measures), to verify the degree to which some dimensions gained/lost importance in the multidimensional poverty composition of the Portuguese population. Furthermore, a possible extension to this work could be a decomposition of results by gender and by age categories, which would provide further insight into the Portuguese poverty setting.

4.2 Assessing the Effects of Government Taxation on Poverty, through CEQ Fiscal Incidence Analysis

Performing fiscal incidence analysis in Portugal, particularly by shedding light in issues such as income inequality and poverty, would not only be of extreme relevance to our country and its citizens, but would also contribute to evaluation efforts of redistributive policies based on taxation, making them more effective in targeting and benefiting the poor.

The basis to employ the CEQ methodology for this issue lies in the decomposition of income into “income concepts” (refer to Figure 2 for more details on the concept), which is basically an accounting approach that decomposes gross income into disposable income by separating transfers and taxes components.

Currently, in Portugal, no source of data provides information on income decomposition as required by the method. As mentioned in Section 3.3, income tax data, IRS, in Portugal should include income components in the near future.

An option to perform this study with the available data would be leveraging on Base de População Residente. However, this source could not be used on its own, since it does not contain information on individual earnings. It had to be merged with another data source, for instance with *Declarações Mensais de Rendimentos da Autoridade Tributária*, an administrative tax dataset being gradually explored by INE. In principle, there would be no need to merge further with household survey data since BPR already contains some information on socioeconomic and demographic characteristics.

Another alternative would be using IRS tax data once income components are specified, and merge it with microdata from household surveys such as ICOR (individual identifiers would need to be consistent across sources though). Survey Correction Methods could be employed to guarantee an accurate portrait of the top of the income distribution and the quality of distributional estimates (more details on this procedure in Section 4.3).

Once the data is established, the core indicators for this analysis are the fiscal impoverishment measure (Higgins and Lustig, 2016), which allows to assess whether the tax and transfer system makes some of the poor poorer and/or some the non-poor poor. The intuition behind this indicator can be visualized in Figure 8.

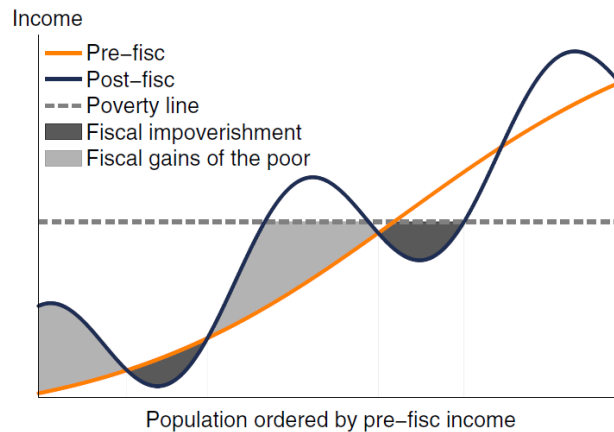


Figure 8: Stylized representation of the pre- and post-fiscal incomes of a population ordered by pre-fiscal income. (Source: Higgins and Lustig, 2016)

The increasing curve represents pre-fiscal income, the wavy curve post-fiscal income, and the dashed line the poverty line; because some individuals receive more in transfers than they pay in taxes, while others pay more in taxes than they receive in transfers, the post-fiscal income curve is sometimes above and sometimes below the pre-fiscal income curve. Although post-fiscal poverty is lower than pre-fiscal poverty because the losses of some poor are more than compensated by the gains of other poor, there is fiscal impoverishment. The extent of it is shown by the dark-shaded areas, while the light-shaded areas represent the extent of fiscal gains of the poor.

Furthermore, this methodology also allows to study the social groups that are getting more benefited from the redistribution system, by comparing the share of total direct transfers received by each income group with the share of total direct taxes payed and with the relative size of each group considered. Finally, to assess whether fiscal interventions make the whole fiscal system more equal, the method consists of analysing marginal contributions, which are equivalent to calculate the difference in inequality measures such as the Gini Index without and with a specific tax or transfer, by taking disposable income as the relevant end income concept, first, and consumable income, secondly.

4.3 Blanchet et al. (2022) Survey Correction Method using Portuguese Data

Portuguese survey data is quite abundant and rich in all the dimensions that were mentioned in the poverty measurement chapter. Its main weakness though, as reported in previous sections, revolves around the undercoverage and underreporting of top incomes, which ends up distorting distributional estimates and effects directly measures of income inequality and poverty.

Thus, to deal with this, one could apply the Survey Correction Method detailed in Section 2.3.

In Portugal, this methodology would most benefit ICOR, a source of survey data which includes variables on income, by correcting the bias with tax data such as IRS.

To obtain the merging point, one needs to compute the survey density and the tax data density for the corresponding income variables and obtain the bias and cumulative bias functions, this latter given by the ratio between the cumulative density function of the survey data (ICOR) and the cumulative density function of the tax data (IRS). The merging point should be the highest value of income such that the cumulative bias function equals the bias function.

The reweighting step should follow the procedure described in detail in Section 2.3. This is:

1. Discretize the distribution of the income variable. In IRS, this should be easier since the

global income variable is not specified in brackets. Thus, there is no need to first convert tabulated forms into continuous distributions to then discretize.

2. Obtain the distribution discretized over a narrow grid made up of all percentiles from 0% to 99%, 99.1% to 99.%, 99.91% to 99.99% and 99.991% to 99.999%, while discarding tax brackets below the merging point.
3. Match the survey data to their corresponding tax bracket.
4. Create dummy variables b_1, \dots, b_m for each income bracket.
5. For all the observations below the merging point, the dummy variables b_1, \dots, b_m are all equal to zero, so the weight adjustment only depends on a constant and possibly other calibration variables such as age and gender, but not income. This procedure, by construction, avoids distorting the bottom of the distribution because it is not necessary to enforce the constraints of the calibration problem. In practice, this enforces the income distribution through a histogram approximation of it.

Finally, to fulfill the replacing step we should inflate the number of data points in the survey by making duplicates of each observation, by attributing to each new observation the weight $q_i = w_i/k_i$, where w_i is the calibrated weight from the previous step, $k_i = \lceil \pi w_i \rceil$ and $\lceil x \rceil$ is x rounded to the nearest integer. Therefore all new observations have an approximately equal weight close to $1/\pi$). The size of the new dataset, made out of the duplicated observations, can be made arbitrarily high by adjusting π .

If each observation is attributed the average income of their population share in the tax data, then by construction the income distribution of the newly created survey will be the same as in the tax data. The last step is to rank observations in increasing order by income to preserve the joint distribution between income and the covariates in the survey.

5 Conclusion

Poverty entails much more than the lack of income and productive resources to ensure sustainable livelihoods. Its manifestations range from hunger and malnutrition in more severe cases such as the one experienced in developing countries, to limited access to education and other basic services, social discrimination and exclusion as well as the lack of participation in decision-making.

Poverty eradication has been mainstreamed into the national policies and actions in accordance with the internationally agreed development goals forming part of the broad United Nations Development Agenda, forged at UN conferences and summits in the economic, social and related fields.

A social perspective on development requires addressing poverty in all its dimensions. Particularly, an integrated strategy towards poverty eradication necessitates implementing policies geared to more equitable distribution of wealth and income and social protection coverage. Most importantly, a social perspective on poverty should contribute to the debate on the effectiveness and limitations of current poverty reduction strategies. Poverty analysis from a social perspective requires thorough examination of the impact of economic and social policies on the poor and other vulnerable social groups.

Nevertheless, the multidimensional analysis of policy impact and investment decisions on poverty reduction is a highly complex task, built on possibly contentious assumptions and extremely demanding data requirements.

In this field, Portugal's information and statistics systems are among the best in the world, containing relevant and accessible information which allow rigorous analyses of policy reduction policies. This data setting should be harvested to its full potential, by contributing to more effective and innovative policy evaluation efforts in the country. In order to seize the data capabilities the most, state-of-the-art methods found in academia should replace the traditional techniques currently employed in the public sector, conducting to a structural reform in the way evaluation is carried out in Portugal.

The aim of this report was to propose alternative and cutting-edge methods to conduct poverty analysis and measurement, while exploring and building on the existing Portuguese data resources to perform such studies.

We proposed three fitting methodologies: the first 2 pertain to poverty assessment through different lenses; the last one deals with a crucial and universal data correction which enables a more precise assessment of poverty.

The Alkire-Foster methodology, particularly through the three experimental indices put forward by Alkire et al. (2014), is a flexible methodology which incorporates the several dimensions

of poverty. Its versatile design accomodates different weights, cut-offs and indicators, which provide an overall view of the poverty situation of each country. Moreover, the measurements developed by the authors, such as the censored and uncensored (raw) headcount ratios, allow for further dissection into the poverty composition experienced by the poor population in a given country. The CEQ methodology constitutes a vital and precise guide into fiscal incidence analysis, enabling governments to assess how effective their current fiscal policies are in achieving their distributional objectives and accelerating poverty reduction. Developed by Lustig (2016), this methodology is fitting for quantifying fiscal impoverishment, that is, an assessment of whether poor individuals were made poorer or non-poor individuals were made poor by the net effect of taxation and public spending, or to study which social groups benefit the most from the current redistribution system. The study of poverty through a fiscal perspective in Portugal would most definitely lead to crucial insights, which could later be incorporated in poverty reduction policies, particularly those based on the redistribution systems. Finally, to address one of the most common shortcomings of data to perform analyses based on income, we present a Survey Correction Method, developed by Blanchet et al. (2022), a meticulous and detail-oriented approach to deal with the fact that income distributions obtained through surveys are usually top-coded - the “missing rich” problem as referred in Lustig (2016). This innovative method has a solid theoretical background which is translated into a practical application to real-life data.

After a deep analysis of the proposed methods for poverty measurement, we provide a comprehensive review of the most relevant and rich databases available in Portugal for poverty assessment purposes. The selected databases were:

- **Quadros de Pessoal**, a linked employer-employee cross-sectional dataset, with information collected since 1986. This data can be appended to create a panel, which allows to track workers across time. It is reported by the firm, which minimizes self-reporting biases.
- **Census data**, an extensive population survey conducted every 10 years, starting in 1981, with information on demographic characteristics and living conditions of the population.
- **Income tax data**, *IRS*, an administrative dataset with information collected since 2014. Income decomposition into the several components should be available soon, but for now the only measure of income aggregates all components into global income.
- **Inquérito às Condições de Vida e Rendimento**, ICOR, is incorporated in the EU-SILC Income and Living Conditions Surveys. It has been conducted in Portugal since 2004. Its methodological process ensures that each household is tracked across 4 years. The scope of this survey is to provide a comprehensive portrait of the living conditions of the Portuguese population.
- **Base de População Residente** is an harmonized dataset which integrates data from Census and administrative information from different sources of the Public Administration. This is done by associating each individual identifier across the databases, through record

linkage and matching. This database includes information on the population residing in Portugal and covers a set of geographic, demographic and socioeconomic characteristics.

Finally, we elaborate on how we could use the several existing databases and leverage them to conduct the poverty analyses suggested previously.

- Alkire et al. (2014) indices' were already constructed using EU-SILC data, so ICOR should provide a perfect match for the implementation of the three experimental multidimensional poverty indices. The authors also provide in their paper some guidelines for the choice of weights and cut-offs.
- The CEQ methodology put forward by Lustig (2016) should incorporate a source of household survey data and a source administrative tax data which allows to decompose income variables into "income concepts". For the time being IRS does not include information on the income composition of individuals, only an aggregate measure of global income. Even when this decomposition is available, IRS tax data individual identifier does not match ICOR's so this approach would be unfeasible. Therefore, the best way to proceed would be to leverage on Base de População Residente, which contains variables included in household surveys which pertain to sociodemographic indicators and some sources of administrative data. Depending on the income variables available, it is likely to have to merge BPR to *Declarações Mensais de Rendimentos da Autoridade Tributária*, to provide measures on earnings, compute the necessary "income concepts" and perform the rest of the analysis.
- Finally, the Survey Correction Method developed by Blanchet et al.(2022) should incorporate administrative tax information to correct survey data, so the best approach in Portugal would be to combine IRS tax data and EU-SILC Living Conditions Survey, ICOR. The method is thoroughly described in Section 4.

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