Analyzing tax-benefit microsimulation with nonparametric methods

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Abstract

The 1998 Italian personal income tax reform is analyzed using an arithmetic tax-benefit model and nonparametric methods, which allow one to detect the impact of tax-benefit policies without specifying any particular relationship or structure in the data.

It is found that the tax system plays a role in the emergence of bimodality in Italian disposable income distribution, that low-income non-working households are among the main losers from the reform, and that changes in tax brackets were more effective than changes in tax credits in modifying the overall distribution of equivalent income.

Keywords: tax-benefit microsimulation model, tax reform, nonparametric regression, kernel density estimation

JEL codes: D31, D63, E62, C14

1 Introduction

Arithmetic tax-benefit microsimulation models analyze the “morning after” impact of tax-benefit reforms on the distribution of income and on poverty, and allow one to assess who are the gainers and the losers. Arithmetic tax-benefit microsimulation models (henceforth, MSM) are mostly developed from household survey databases, which provide a picture of the population much closer to reality than any database using representative households. Nowadays, most developed countries have at least one MSM and multi-country models have also been developed (e.g., EUROMOD, a Europe-wide tax-benefit model Sutherland, 2001). They are important tools for orienting and evaluating tax and benefit policies.

The output of MSM is often presented using distributions by deciles or by histograms. However, as discussed in Silverman (1986, Ch. 2), these methods often provide a biased and non-robust picture of reality. Nonparametric methods allow one to describe data distribution and relationships simply by letting the data speak by themselves, without specifying any particular relationship or structure in the data, without defining *a priori* the origin of data and the number of data intervals to be considered.

Nonparametric density estimation can be regarded as a development of the intuitive histogram technique for density estimation. In contrast to histograms, nonparametric density estimation does not suffer major limitations such as choice of origin, limited robustness of estimates, ragged picture, absence of derivative and low flexibility for multivariate density analysis. The interpolation of pointwise estimation of density provides a smooth picture, useful in detecting unusual behavior of the distribution such as bimodality.

Nonparametric density estimation has proven to be an effective research tool in economics. For instance, in income inequality literature kernel estimation has been used to show the evolution of disposable income distributions from a unimodal to a bimodal shape. Cowell et al. (1996); Jenkins (1994) among others called this phenomenon the "shrinking of the middle class". They showed that the widening gap between least and most well-off households in the UK was mainly due to stagnating income of non-working and relatively large households opposed to dynamic earnings of working households. Pudney (1993) used nonparametric methods to analyze income and wealth inequality in the life-cycle using Chinese data: he found that only a small part of observed inequality can be explained by life-cycle factors in contrast to what other authors had found using dummy-variable regression methods. In the empirical growth literature Quah (1997) used nonparametric estimation to point out the emergence of a "twin peaks effect" - the clustering of a large number of countries at lower per capita income and the increasing gap between poor and rich countries. In labor economics DiNardo et al. (1996) used propensity score methods and nonparametric density estimations to show the importance of institutional factors, such as unionization and minimum wage, for the evolution of wage distribution in the US labor market.

This paper suggests a combination of MSM and the descriptive power of non-parametric methods to analyze tax policies, a combination never suggested before.

The 1998 Italian personal income tax reform is simulated, along with a counterfactual tax system, by using an arithmetic tax-benefit microsimulation model. Nonparametric density estimation is used to investigate whether the tax system had any impact for the bimodality of after-tax income density, which was highlighted by D'Ambrosio (2001) and Pittau and Zelli (2001). The 1998 reform increased tax liabilities, mainly by increasing the tax rate of the first bracket. In order to offset the negative effects on poor household income, tax credits were selectively increased. Nonparametric regression methods are used to analyze losers and gainers by sample subgroups and different levels of income and by assessing whether increased tax credits were able to completely offset increased tax liability for all poor households.

The structure of the paper is as follows. Section 2 describes the data set, the microsimulation model used and the main elements of the 1998 IRPEF reform. Section 3 presents the first simulation exercises, assessing the impact of the 1998 tax reform in income distribution, by household types. Section 4 decomposes the fiscal reform assessing the relative importance of tax credits and tax brackets changes. Section 5 concludes.

2 The data set, the microsimulation model and the 1998 IRPEF reform

The data set used here is the 1998 Survey of Household Income and Wealth (SHIW). It is published by the Bank of Italy and based on face-to-face interviews. The SHIW is a long standing survey: it was started in the mid 1960s, was run about annually up to 1987, henceforth about every two years. At present the SHIW is the main, if not the only, data set for Italian household MSM and among the most frequently used for any kind of household income analysis at the national level in Italy (for a review of other data sets, see Brandolini, 1999).

The 1998 data set collects detailed micro data for about 7,147 households and 20,901 individuals on 1998 disposable income, consumption, labor market, monetary and financial variables. The sample was drawn in two stages (municipalities and households) with the stratification of the primary sampling units (municipalities) by units and size, to make it representative of the national population. Households were then selected randomly and a sampling weight, defined as the inverse of the probability of inclusion of each household in the sample, was attached to each observation. Data are checked before release: the strategy is either to drop the interview for the whole household if missing data cannot be reasonably inferred from other characteristics of the individual/household or to impute the missing data, by using regression models conditional on socio-demographic characteristics of the individual/household involved. Data imputation is less than 0.1% for most variables (Banca d'Italia, 2000, p. 35). The interviews include only recall questions, and do not include information about people who do not have a registered dwelling or are in a hospital or other kind of institution.

As for the limitations which are more relevant for MSM, the main one refers to the type of income recorded: it refers to disposable income, excluding taxes and social contributions paid and benefit received. Hence, the first role of a MSM on SHIW data is to simulate the before-tax income, prior to introducing any other policy simulation.

The MSM used here is TABEITA98, a TAx-BEnefit microsimulation model on ITAlian 1998 SHIW data. TABEITA98 simulates 1998 personal income taxation (IRPEF and "imposte sostitutive")[1] net of social contributions. TABEITA98 is a static model without behavioral response. It can be described as a deterministic transformation of a given sample into a new one. Let $\mathbf{Y^A}$ and $\mathbf{Y^B}$ be the $N \times 1$ vectors of after-tax (AT) and before-tax (BT) income, respectively: the former vector is obtained from the latter through a tax transformation, say τ_i, $i = 1, 2..., N$, where N is the number of individuals in the sample. Since the data are net of taxes and social contributions, the first role of the model is to recover individual BT income:

$$Y_i^B = \tau_i^{-1}(Y_i^A) \tag{1}$$

for all $i = 1, ...N$. There are two major complications here. First, the tax transformation τ_i is not the same for all individuals. Personal income taxation in Italy is on individual base and is progressive. Progressivity is obtained mainly by an increasing tax-bracket structure and by tax credits which depend on the type of income and household characteristics of the taxpayer. The tax transformation τ_i in (1) is highly non linear. This implies that y_B has to be obtained numerically, by recursive approximations.

In this model the main assumptions are that (a) the sample is representative of the population, (b) the tax and benefit legislation, τ_i, is perfectly known by the individual and applied without error. Although the first assumption is granted by the Bank of Italy who produced the data, the second is meant to keep variability to a minimum. An alternative solution would be to randomly include errors in the model assessing the relevance of such changes in the MSM. Here, instead, only systematic errors leading to under- or over-reporting are considered and the final model is calibrated on actual data coming from Italian Ministry of Finance. The probability of programming mistakes is kept to a minimum with a number of checks and a validation procedure.

The model allows one to compute the amount of tax credits, of tax base deductions, of personal income tax paid, the BT income (divided into five components: (i) employment, (ii) self-employment, (iii) pension, (iv) rental and estate and (v) capital, interests and participation), transfers and other incomes not liable to personal income tax. All incomes can be computed at the individual and household level, allowing for different equivalence scales.

Because of the financial and currency crisis that hit Italy in 1992, several tax policies were introduced during the 1990s, affecting both direct and indirect taxation. In particular, two clearly different periods may be distinguished: the first up to 1996 and the second starting from 1996. The first of these periods was characterized by constant political instability and frequent changes of the Minister of Finance, with several temporary taxes without a clear overall design, while during the second higher political stability favored the design of a comprehensive tax reform. Here, the focus will be on some aspects of the 1997-98 IRPEF tax reform, and their effects on Italian households.

The two main novelties of the 1998 IRPEF reform with respect to previous years IRPEF concern the modification of the tax brackets and of the tax credits structure, while no relevant change in the income base definition was introduced. As shown in Appendix A, the number of fiscal brackets were reduced, from seven to five, with the reduction of the highest tax rate (from 50% in 1991 to 45.5% in 1998), the increase of the first tax rate (from 10% in 1991 to 18.5% in 1998) and a substantial change of the others. Tax credit for employment and self employment were increased in amount and in number, tax credits for "family burdens" were increased, a new tax credit for pension recipient was introduced depending on income and a few other attributes. The government which passed the reform claimed that the increase in tax credits would have offset the effect of increased rate of the first tax bracket.

These topics have been analyzed by other authors. Among others, Bosi et al. (1999), CER (1998b) and Birindelli et al. (1998) studied the 1998 reform compared with the previous year legislation, while Giannini and Guerra (1999) compared 1999 taxation system with the 1990 one. They all conclude that the reform caused an overall increase of IRPEF liability on Italian households but there is less agreement in detecting the most and least affected groups dividing the sample by area of residence and the occupation of the household head. Moreover the results are at times numerically quite different and an abundance of numbers tends to obscure the main picture of the distributional effects of the reforms.

3 Simulating a counterfactual tax system

In this section TABEITA98 is employed for comparing the 1998 with the 1991 IRPEF system, weighted by CPI.

In the first stage, using the after-tax income data contained in the N-dimensional 1998 SHIW sample (Y_{A98j}, $j = 1, ..., N$) and the 1998 IRPEF legislation, the MSM is used to obtain the BT income (Y_{B98j}). In the second stage, the counterfactual estimation is performed starting from 1998 BT income (Y_{B98j}, for $j = 1, ..., N$), simulating 1991 IRPEF system. The year 1991 was considered as the comparison year since 1992 is regarded as the year before the "turning point" of Italian public finance management. The year 1991 is the last year before the financial and currency crisis and that prompted the recovery process. The counterfactual distribution can be described as the "distribution of income that would have prevailed in 1998 if personal taxation had been replaced by 1991 IRPEF and each income recipient had obtained exactly the same income, before personal taxation". It is however not claimed that this simulation is fully suitable to compare 1998 and 1991 Italian personal income taxation because behavioral response to taxation are not estimated.

Given the focus on household welfare, the Italian Poverty Commission equivalence scale, derived from the Engel methodology, is conventionally adopted, assuming equal distribution among members of household income. It requires the elasticity of total consumption on family magnitudes to be estimated by a weighted regression with the proportion of food expenditure on household expenditure (c_f) as dependent variable, and the log of total household expenditure (c) and the log of the number of the members of the household (m) as regressors (De Santis, 1998):

$$c_f = \gamma_0 + \gamma_1 \ln c + \gamma_2 \ln m + u$$

The elasticity estimate is obtained as $\varepsilon = (-\gamma_2/\gamma_1)$ and the equivalent income of each member of household h can be estimated as:

$$X_h = \frac{Y_h}{m^{\varepsilon}} \tag{2}$$

where Y_h is the sum of all incomes in household h. From the regression performed on 1998 SHIW data, an elasticity equal to 0.757 was obtained.

3.1 The density estimation technique

The nonparametric density estimation method used here is derived from a generalization of the adaptive kernel density estimator to take into account sampling weights. The adaptive kernel is obtained in a two-stage procedure. In the first stage, a pilot estimate with fixed-bandwidth is performed to get a rough idea of the density along the data range. In the second stage, the fixed bandwidth parameter is replaced by a function of the fixed-bandwidth and of the pilot density estimation such that the bandwidth is larger where the pilot density estimate is smaller (i.e. the data are more sparse), and is smaller where density estimation is larger (i.e. the data are more concentrated). Such an estimation technique is particularly suitable for thick-tailed distributions such as income densities, since a variable bandwidth tends to dampen fluctuations in the tails and increase precision in the bulk of the distribution. In detail the procedure is as follows (Abramson, 1982; Silverman, 1986). Let $\mathbf{X} = \{X_i, i = 1, ..., N\}$ be a univariate random sample from an unknown distribution f. The pilot estimate $\widetilde{f}_N(x)$ to be estimated for the first stage is:

$$\widetilde{f}_N(x) = \frac{1}{Nh_N} \sum_{i=1}^{N} K\left(\frac{x - X_i}{h_N}\right)$$

where h_N is a fixed-bandwidth, K is the kernel function and $\widetilde{f}_N(X_i) > 0$ for all i.

The second stage begins with the estimation of a local bandwidth factor λ_i :

$$\lambda_i = \left(\frac{\widetilde{f}_N(X_i)}{g}\right)^{\alpha}$$

where $0 \leq \alpha \leq 1$, and g is the geometric mean of $\widetilde{f}_N(X_i)$,:

$$g = \Pi_{i=1}^{N} \left(\widetilde{f}_N(X_i)\right)^{1/N}$$

The final estimation $\widehat{f}_N$ is given by:

$$\widehat{f}_N(x) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{h_N \lambda_i} K\left(\frac{x - X_i}{h_N \lambda_i}\right)$$

The adaptive kernel can then be modified to take into account the sampling weights, θ_i, normalized to sum to N. Every observation is then weighted by $\frac{\theta_i}{N}$ and not by $\frac{1}{N}$ implying that (3.1) becomes:

$$\widehat{f}(x) = \frac{1}{Nh_N} \sum_{i=1}^{N} \theta_i K\left(\frac{x - X_i}{h_N}\right)$$

then (3.1) becomes:

$$\widehat{f}_a(x) = \frac{1}{N}\sum_{i=1}^{N}\frac{\theta_i}{h_N\lambda_i}K\left(\frac{x-X_i}{h_N\lambda_i}\right)$$

The choice of the bandwidth parameter h_N is a delicate issue: a larger than optimal h_N will oversmooth the density increasing the bias, a smaller than optimal h_N will increase the variance of the estimate reducing the bias. Moreover, it was proved that the optimal bandwidth, defined as the parameter that minimizes the mean integrated square error, depends on the unknown density being estimated (Parzen, 1962). Among the various optimal bandwidth parameter proposed in the literature,[2] The the Silverman's rule-of-thumb bandwidth is chosen here:

$$h_N = 0.9A(n)^{(1/5)} \tag{3}$$

where $A = min\{\text{standard deviation, interquantile range}/1.34\}$ is an adaptive estimate of spread. This bandwidth parameter was proposed by Silverman (1986, p. 48) as a parameter that copes well with a wide range of densities and is trivial to compute. However, other bandwidth have also been used and some results to follow will be presented for bandwidths that are equal to a given proportion of the optimal bandwidth in (3).

Making the local bandwidth factor dependent on a power of the pilot density gives flexibility in the design of the method: the larger the power α, the more sensitive the method will be to variations in the pilot density. Following Silverman (1986, p.48)'s suggestion, it was set at $\alpha = 1/2$.

As for the choice of the kernel function, K, the Epanechnikov kernel was used since it maximizes efficiency (see among others Silverman, 1986, Section 3.3.2).

Finally, in some relevant cases, to assess the reliability of density estimates the 90% confidence bands are computed as 1.645 standard errors around $\widehat{f}_\alpha(x)$.

Standard errors come from the following expression for the variance of $\widehat{f_\alpha}(x)$ given in Burkhauser et al. (1999, p. 261):

$$V(\widehat{f_\alpha}(x)) = \left(\sum_{i=1}^{N} \frac{\theta_i^2}{N^2} \right) \frac{f_\alpha(x)}{h_N \lambda_i} \int \{K(z)\}^2 dz \tag{4}$$

Figure 1 presents density estimations on the whole sample for BT, actual and counterfactual AT income distributions with three different bandwidths: h equal to the Silverman's optimal bandwidth (3), $h_2 = 0.75h$ and $h_3 = 2h$. This figure produces a clear picture of the concentration effect induced by personal income taxation: the 1998 BT income density presents a lower maximum and a higher mode than AT income. The AT density presents a thinner upper tail than the BT income density, showing that the 1998 IRPEF system is very effective in reducing the overall density at medium-high income. AT income density is clearly bimodal if h_N is equal to or smaller than the Silverman's bandwidth (3). This result add something to findings of Pittau and Zelli (2001) and D'Ambrosio (2001): the bimodality of equivalent AT income is partly due to and magnified by personal income taxation.

The comparisons between the actual and the counterfactual AT income distributions show that the counterfactual AT density reaches lower maxima than the actual 1998 AT income density, although the location of the modes do not widely change.

The last panel of Figure 1 depicts the difference between counterfactual and actual AT distributions for the three bandwidths considered. It shows that density at income levels below about Lit 18 millions (approximately €9,000) was higher in 1998 than with the counterfactual 1991 tax system. Given this pattern we can reasonably expect that inequality indices will show a decreasing trend from BT income to counterfactual AT income and to actual AT income, as shown in Appendix B. Another relevant issue is clearly evident from the kernel density estimation: the Italian personal personal income tax does not effectively help reducing poverty. In fact the BT income density at zero equivalent income is different from zero, showing that there are households with zero income. However, BT and AT incomes do not differ at zero equivalent income level. This is mainly due to the fact that IRPEF does not allow tax credits in case of negative or zero tax liability.[3]

Table 1 about here.

Figure 1 about here.

3.2 Decomposing the sample

Other interesting observations can be provided breaking down the sample by occupation of the householder. Figure 2 depicts the actual and counterfactual AT density estimates with a bandwidth as in (3) using continuous and dashed lines, respectively. Thinner lines are the 90% confidence bands of the two density estimates. Figure 2 shows that bimodality of AT income is very clear in employed household and is nearly absent in pensioner households; bimodality is less evident in the self-employed and the residual ("other") subsamples. However, the estimation of confidence bands does not allows us to reject the hypothesis that the actual and counterfactual AT distributions are the same.[4] This is possibly due to the fact that the actual and counterfactual tax systems do not present huge differences but also to the fact that sizes of subsamples are not large enough.

Figure 2 about here.

The difference of pointwise density estimation depicted in Figure 3 shows that the difference is at first negative and becomes positive at higher levels of income for all subsamples, although it obviously presents more fluctuations the smaller is the bandwidth, showing a compression of the upper tail of income distribution and an increased concentration around the mode.

Figure 3 about here.

3.3 Losers and gainers

Figures such as Figure 3 do not allow one to say who the losers and winners are after the 1998 income tax reform. They only estimate the difference between two density estimates, without consideration of possible re-ranking occurring by applying two different tax systems on the same vector of BT income.

An analysis of losers and gainers is performed analyzing the joint distribution of X and Y, where X is the actual 1998 BT income and Y is the difference between counterfactual and actual 1998 AT income relative to 1998 BT income, i.e. the relative loss of income caused by the 1998 personal taxation system. Given the N pairs $\{x_i, y_i, i = 1, ..., N\}$, the relationship between Y and X can be estimated as:

$$\begin{aligned} y_i &= m(x_i) + \epsilon_i \qquad (5) \\ E(Y|X = x) &= m(x) \qquad (6) \end{aligned}$$

where ϵ_i is a random error. The estimation of $m(x)$ is then performed non-parametrically using the Nadaraya-Watson estimator. As in the kernel density estimation, the bandwidth h_N determines the degree of smoothing of $\widehat{m}$. As the h_N goes to zero, $\widehat{m}(X_i)$ converges to Y_i, i.e. an interpolation of the data is obtained. On the other hand, if h_N goes to infinity the estimator is a constant function that assigns the sample mean of Y to each x (see, among others Härdle et al., 2004). Choosing the smoothing parameter for the covariate vector is again a crucial problem: as before the Silverman's rule-of-thumb bandwidth (3) was first used, and the sensitivity of the estimates to different bandwidths analyzed by considering different proportions of the initial bandwidth.

Figure 5 shows the results on the whole sample of a nonparametric regression of the relative loss caused by 1998 tax system on 1998 BT income for different values of the bandwidth, i.e. a nonparametric regression of Y over X as defined above. It shows that those in the lowest part of the income range suffered the highest relative loss: in some cases they had to pay up to 6-8% more with 1998 personal income reform than with the counterfactual income. This is very likely to be due to the increased first tax rate of the 1998 reform but also to the change in tax credits (See Appendix A). The relative loss is the lowest for equivalent income of about 10 millions Lit and increasing afterwards.

Figure 4 about here.

It should be noted that some households have been affected by the reform more than others. In Figure 5 the nonparametric regression by occupation of the householder are reported with a bandwidth chosen as in (3) and 90% confidence bands. Relative loss was increasing from zero level for employed, but it was higher than average for poor pensioner households and the residual ("other") group and for some of the self-employed households below 20 millions Lit.

Estimates are reasonably reliable with the only exception of higher incomes in the residual group due to the small sample size. These results show that the probability of experiencing poverty is higher after the reform than before it especially for households with a non-employed head. This result is likely to come from the fact that the "entry" marginal tax rate in 1998 (18.5%) was higher than that in 1991 (10%) for all taxpayers, while tax credits were increased mostly for working taxpayers.

Figure 5 about here.

3.4 A revenue-neutral reform simulation

Since the 1998 IRPEF reform induced a relevant increase of revenue compared to the 1991 system, two different revenue-neutral simulations were performed. In the first of these the 1998 excess revenue is distributed equally to each individual in the population, in the second the excess revenue is distributed to each individual in proportion to her BT income.

It is of course difficult to assess how the increased tax revenue was employed, partly because other tax and welfare reforms were introduced in the same period, and partly because the increased tax revenue was not constrained to be used for any particular policy. However one can for instance assume that redistribution happens in cash or in kind or in reductions of other taxes liabilities.

A lump-sum redistribution of excess revenue, if compared to 1998 actual AT income, would induce a reduction of the density at a lower levels of income and an increase in the mode of the distribution, due to a shift of the former distribution to the left (Figure 6).

Figure 6 about here.

A proportional redistribution have a slightly smaller effect on equivalent income distribution (Figure 7), showing that the excess revenue of 1998 IRPEF compared with 1991 IRPEF revenue closer to a proportional (to BT income) increase of tax liability rather than to an equal increase of tax liability for all.

4 Decomposing the fiscal reform

The difference between the counterfactual and actual densities was decomposed to investigate the overall overall importance of tax credits for altering the shape of income distribution and inequality, as opposed to that of the bracket structure.

Using $\beta_d = 98$ to denote the set of tax credits from gross tax liability in 1998, $\beta_b = 98$ the tax bracket structure of 1998 and similarly for 1991, and $f(.)$ the density function, the difference between the two densities mentioned earlier can be represented as in equation (7) and decomposed as in (8)-(9) or as in (10)-(11).

$$f(Y_A; \beta_d = 91, \beta_b = 91) - f(Y_A; \beta_d = 98, \beta_b = 98) = \tag{7}$$

$$[f(Y_A; \beta_d = 91, \beta_b = 91) - f(Y_A; \beta_d = 98, \beta_b = 91)] + \tag{8}$$

$$[f(Y_A; \beta_d = 98, \beta_b = 91) - f(Y_A; \beta_d = 98, \beta_b = 98)] = \tag{9}$$

$$[f(Y_A; \beta_d = 91, \beta_b = 91) - f(Y_A; \beta_d = 91, \beta_b = 98)] + \tag{10}$$

$$[f(Y_A; \beta_d = 91, \beta_b = 98) - f(Y_A; \beta_d = 98, \beta_b = 98)] \tag{11}$$

For instance, line (9) presents the difference between a counterfactual AT income density, which was obtained using the 1998 tax credit system and the 1991 IRPEF brackets, and the actual 1998 AT income density.

In the last part of this paper two alternative scenarios are simulated, both on 1998 data. Scenario 1 is characterized by a tax credit system equal to the one actually in use in 1991 but with an income bracket structure and tax rates like that in 1998 (i.e. the first part of (11)). On the other hand, Scenario 2 considers the case in which the tax credit system is like that in 1998 and the income brackets structure and tax rates as in 1991 (the first part of (9)).

These simulations have been analyzed by using nonparametric regression. In Figure 8 the relative loss variable, Y is defined as the difference between Scenario 1 and actual AT income (i.e. the difference in line 11) relative to actual BT income. Figure 8 shows that had tax credits been as in 1991, the average loss of households with equivalent income higher than 20 millions Lit would have been about zero. However, on average poorest households would have suffered significant losses because of tax credits higher than in 1998.

Figure 8 about here.

In Figure 9 the relative loss variable, Y is defined as the difference between Scenario 2 and actual AT income (i.e. the difference in line 9) relative to actual BT income. Figure 9 shows that had tax brackets and tax rates been set at the 1991 level, losses would have been more evenly spread across different levels of income and would approximately average 3%. The lower than average losses of equivalent income below 10 millions Lit are likely to be due to the effect of 1998 tax credits.

Figure 9 about here.

5 Conclusions

This paper suggests to use nonparametric methods to analyze tax-benefit reforms, as they can increase the understanding and access of tax-benefit microsimulation results and provide useful insights about the impact of tax-benefit reforms on income distribution, poverty and analysis of losers and gainers.

Simulating AT income for 1998, the strong concentration effect induced by the progressive tax system is illustrated. The combination of microsimulation and nonparametric density estimation allows one to show that the 1998 IRPEF system increased the concentration around the mode with respect to the updated 1991 IRPEF system. The higher concentration is obtained with a movement of part of the density mass from upper to lower levels of equivalent income, resulting in an overall decrease of inequality. Nonparametric density estimation also shows that personal income taxation has an important role for the emergence of bimodality in the Italian AT equivalent income density.

Decomposing the sample into different subgroups, it is shown that some households have been affected differently from others. While poor employed households were basically unaffected by the reform, those with non-working head suffered major losses increasing their probability of experiencing poverty. In fact, for these groups of households the increased tax credits were not enough to offset the increased tax rate of the first income bracket.

Finally, it is shown that the increased tax liability was roughly proportionally spread across tax payers and that changes in income brackets were more effective in changing the overall distribution of equivalent income than changes in tax credits.

Appendix A

1998 IRPEF vs. counterfactual 1991 IRPEF

The following tables provide some detail about the difference between the 1991 and the 1998 legislations. In 1998, tax brackets are reduced from seven to five (Table 2). For a fiscally dependent spouse, tax credit depends on BT income (Table 3). Tax credit for dependent children and other dependent relatives do not depend on BT income (Table 4). Tax credit for employment and self-employment income are different and depend on income (Table 5). If the taxpayer receives only a pension income smaller than Lit 18 million, and she does not own any other building except her own dwelling, there is an additional tax credit equal to Lit 70,000 in 1998.

Tables 2-6 about here.

Appendix B

Inequality analysis of BT, actual and counterfactual AT income

A traditional analysis of inequality of BT, actual and counterfactual AT income can be performed using Lorenz curves.

Provided that the density function is non zero throughout the range $[Y_1, Y_N]$, where N is the number of observation, and $Y_1 < Y_N$, then for each $p \in (0,1)$, there is just one income level y, which satisfies $p = F(y)$, the income of the first $100p$ percent of income recipients is $N \int_0^y yf(y)dy$ and the total income is $N \int_0^\infty yf(y)dy = N\mu$, where μ is the mean income (Lambert, 1993). Hence, using $\widehat{f}(y)$ for the density estimation of income, a finite-sample Lorenz curve $L(p)$ is defined by

$$p = F(y) \Rightarrow L(p) = \frac{1}{N} \sum_{j=1}^{J} \frac{X_i \widehat{f}(X_i)}{N}, 0 < p < 1$$

In Table 7 the Lorenz curve for BT income, counterfactual AT income and actual AT income is provided. Lorenz curves do not cross, i.e. 1998 AT income Lorenz-dominate (i.e. is more equally distributed of) the counterfactual AT income, which Lorenz-dominates the 1998 BT income. This results will be confirmed by a large class of inequality indices satisfying axioms of anonymity, mean independence and the transfer principle (Cowell, 1995). In Table 8 some inequality indices are reported: they show, coherently with what stated before, that equality is increased by 1991 IRPEF and even more by 1998 IRPEF.

Tables 7 and 8 about here.

Notes

[1] IRPEF and "imposte sostitutive" on interest and capital gains accounted for 75,8% of 1998 total Italian revenues from direct taxation (Banca d'Italia, 1999).

[2] For an introductory description of the choice of the smoothing parameter, see Silverman (1986, Section 3.4) or Bowman and Azzalini (1997, Section 2.4)

[3] The analysis of Figure 1 is performed without confidence bands mainly for clarity reasons. It should however be noted that the confidence regions greatly overlaps for the two AT densities. BT density is instead significantly different from AT income densities. Finally, confidence bands also show that the density is significantly different from zero at zero income. Figure 1 inclusive of confidence bands can be obtained on request from the author.

[4] Note that confidence bands are different from confidence intervals since confidence bands do not consider the bias. Hall (1992) deals thoroughly with bias removal in confidence interval density estimation either by under-smoothing or by explicit bias removal in the context of fixed bandwidth kernels. However, both methods would increase the complication of the estimation without real benefit for the present analysis.

Tables and figures

Table 1: Abbreviations used in tables and figures

act AT	actual 1998 AT income density, $f(y_{A98})$
ctf AT	countefactual AT income density, $f^c(y_{A91})$
act BT	actual 1998 BT income density, $f(y_{B98})$

Table 2: Actual 1998 and counterfactual structure of IRPEF tax brackets (Lit 1936.27=€1)

1991 IRPEF (Lit ’000)	**Counterfactual** (Lit ’000)	**tax rate** (%)	**1998 IRPEF** (Lit ’000)	**tax rate** (%)
0-6,800	0-8,786	10	15,000	18.5
6,800-13,500	8,876-17,442	22	15,000-30,000	26.5
13,500-33,700	17,442-43,540	26	30,000-60,000	33.5
33,700-67,600	43,540-87,339	33	60,000-135,000	39.5
67,600-168,800	87,339-218,090	40	over 135,000	45.5
168,800-337,700	218,090-436,308	45		
over 337,700	over 436,308	50		

Table 3: Actual 1998 and counterfactual tax credits for dependent spouse (Lit 1936.27=€1)

1991 IRPEF	**tax all.** (Lit ’000)	**Counter. tax all.** (Lit ’000)	**1998 IRPEF** (Lit ’000)	**tax all.** (Lit ’000)
any income	675	872.1	0-30,000	1,057.552
			30,000-60,000	951.552
			60,000-100,000	889.552
			over 100,000	817.552

Table 4: Actual 1998 and counterfactual tax credits for dependent children and other relatives (Lit 1936.27=€1)

	1991 tax all. (Lit '000)	**counterf tax all.** (Lit '000)	**1998 tax all.** (Lit '000)
depend. child	78	101	336
other dep. relative	108	139.5	336

Table 5: Actual 1998 and counterfactual tax credits for employment income. * is an average. The actual tax credit (in Lit '000) was computed as 851-[$(y_B - 12,400) \times 0.78$], where y_B is BT income.

1991 IRPEF (Lit '000)	**Fisc.all.** (Lit '000)	**count. brack.** (Lit '000)	**t.a.** (Lit '000)	**1998 brack.** (Lit '000)	**t.a.** (Lit '000)
12,400	851	16,021	1,099	0-9,100	1,680
12,400-12,659	750**	16,021-16,355	969	9,100-9,300	1,600
over 12,659	648	16,355	837	9,300-15,000	1,500
				15,000-15,300	1,350
				15,300-15,600	1,250
				15,600-15,900	1,150
				15,900-30,000	1,050
				30,000-40,000	950
				40,000-50,000	850
				50,000-60,000	750
				60,000-60,300	650
				60,300-70,000	550
				70,000-80,000	450
				80,000-90,000	350
				90,000-90,400	250
				90,400-100,000.	150
				over 100,000	100

Table 6: Self-employment tax credits. * is an average. The actual tax credit (in Lit '000) was computed as 168-[$(y_B - 6,800) \times 0.78$], where y_B is BT income.

1991 inc. brack (Lit '000)	**tax.all.** (Lit '000)	**Counterf.** (Lit '000)	**t.a.** (Lit '000)	**New IRPEF** (Lit '000)	**t. a.** (Lit '000)
0-6,800	168	0-8,786	217	0-9,100	700
6,800-7,000	90*	8,876-9,044	116	9,100-9,300	600
				9,300-9,600	500
				9,600-9,900	400
				9,900-15,000	300
				15,000-30,000	200
				30,000-60,000	100

Table 7: Lorenz curve for different type income

Pop. share	BT income.	count. AT y	AT y 1998
1/10	0.0117	0.0161	0.0176
2/10	0.0396	0.0560	0.0611
3/10	0.0811	0.1146	0.1247
4/10	0.1363	0.1920	0.2093
5/10	0.2066	0.2880	0.3123
6/10	0.2936	0.4015	0.4315
7/10	0.3997	0.5282	0.5615
8/10	0.5308	0.6631	0.6939
9/10	0.6986	0.8086	0.8313
10/10	1	1	1

Table 8: Some inequality indices for different type of income

	AT income	count AT y	AT income
rel. mean deviation	0.306	0.288	0.285
coeff. of variation	0.923	0.826	0.818
Gini index	0.429	0.404	0.401
Theil entropy meas.	0.325	0.283	0.279
Theil mean log dev.	0.359	0.315	0.312