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WORK INCOME TAX EVASION IN ITALY: ANALYSIS OF REDISTRIBUTIVE EFFECTS

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Work income tax evasion in Italy: analysis of redistributive effects

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1 Introduction

Tax evasion is a serious issue in Italy. According to recent estimates it seems that between 27% and 48% of official Italian GDP is hidden. By using different methodologies, these estimates show that Italy is the country where tax evasion is the highest among major OECD countries (Schneider, 2000a). These figures rise concerns at a macro level, for instance as for the reliability of official statistics and the efficiency of national productions, however they say little as for who are tax evaders and they do not provide much insights about how to develop policies for reducing tax evasion. Measuring tax evasion is a formidable task. Schneider (2000b, p. 1) describes tax evasion measurement "as a scientific passion for knowing the unknown". However, a deeper comprehension of tax evasion is necessary for public policy design and to estimate the bias that tax evasion introduces in many statistics. For instance, let us look at inequality figures. According to recent comparative studies on OECD countries, the highest income inequality is found in the US, followed by the UK and Italy, the latter two presenting similar figures using standard inequality measures (Atkinson et al., 1995; Smeeding, 2000). However, how relevant is the bias due to tax evasion and how much would it modify the inequality figures?

In this paper we provide a first attempt to quantify the effect of tax evasion on inequality indices. Section 2 provides a brief review of recent contributions in the estimation of tax evasion in Italy, focussing mainly on microeconomic approaches and in particular on direct methods of tax evasion estimation. Some of the direct methods of tax evasion estimation are based on the comparison between different data sources under the assumption that the degree of truthfulness of respondents is different depending on whether the interviewer is the fiscal authority or an institution granting anonymity. This methodology will also be used in the rest of this paper. However, before implementing it Section 3 analyses how representative of the underlying population is the survey data set used and a grossing-up procedure is implemented to correct major deviations from true figures. Section 4 presents some estimates of tax evasion focussing on employment and self-employment income. Section 5 shows the extent of tax evasion on inequality indices and finally Section 6 concludes.

2 Available evidence about tax evasion in Italy

There are two main methods to estimate tax evasion: the direct and the indirect approach. Direct methods aim at estimating tax evasion through the use of microdata coming from sample surveys based on voluntary replies or auditing activity conducted by fiscal authorities. Indirect methods deduct tax evasion considering it equal to the difference between aggregated macro indicators, for example discrepancy between income and expenditures or difference between the actual demand for money and the demand for money estimated in absence of taxes (currency demand approach). Many of these methods have been applied to provide a measure of tax evasion in Italy. In particular, Marenzi (1996), Cannari et al. (1995) and Calzaroni (2000) used direct methods while Zizza (2002) and Schneider (2000a), among others, employed an indirect method.

Marenzi (1996) and Cannari et al. (1995) assume that individuals report a more truthful income to an anonymous interviewer than to fiscal authorities. Comparing the Survey of Household Income and Wealth (SHIW) by the Bank of Italy (BI) and the analysis of tax forms by the Ministry of Finance (MF), the former data set provides larger estimates of income variables. The difference between BI and MF disposable income is then considered as hidden income and, loosely speaking, referred to as evasion. Cannari et al. (1995) and Marenzi (1996) considered years 1989 and 1991, respectively. Marenzi (1996) finds evidence of positive tax evasion in the two first deciles of employment income and negative evasion in the following ones, an evasion increasing in the level of income for pension income and a tax evasion that is decreasing, in relative terms, in the level of income for entrepreneurs' and professionals' income. Cannari et al. (1995) reach similar conclusions: tax evasion is on average zero for employment income and increasing in the level of income for professionals and entrepreneurs. As for the issue of how representative of the true population is the survey, Marenzi (1996) does not consider the issue and Cannari et al. (1995) declare to use post-stratification techniques though details are overlooked and a proper analysis of results is difficult.

Calzaroni (2000) uses a different the method to measure the incidence of the hidden economy. Labour supply and labour demand by sectors is estimated from household and firm surveys, respectively and compared at a national and regional level. The difference between the two is considered to be the number of the irregular workers. This figure, multiplied for the average sectorial productivity estimated for regular workers gives a first measure of the underground economy. The overall incidence of the underground economy is calculated integrating this figure with coefficients correcting for the underestimation of the turnover and the balancing between aggregated input and output. The results indicate that, for 1998, the share of the underground economy on GDP in Italy is between 14.7 and 15.4%. Among the major advantages of direct methods is that they are more suitable to discuss the tax evasion phenomenon at the micro level and they can point out directions for policies.

Zizza (2002) and Schneider (2000a), estimate the extent of the aggregate underground economy in Italy using an indirect methods such as the factorial analysis and the currency demand approach. Zizza estimates the share of the underground economy (excluding illegal and criminal activities) on GDP for the years 1984-2000 between a maximum of 17.6% (1991) and a minimum of 14.3% (2000). Schneider's estimates include also the illegal and criminal activities. According to him the share of the underground economy on the italian GDP is very high and increasing (from 25.8% in 1994 to 27.8% in 1998), the highest rate among the OECD countries.

3 The issue of grossing-up

Whenever a direct methodology for tax evasion estimation based on the comparison between a survey-based data set and tax forms is undertaken, it is important to analyze the non-response bias, i.e. the fact that decision to not-respond is not random. The non-response bias is larger the larger is the rate of non-response and the larger are the difference between respondents and non-respondents (see, Little and Rubin, 1987). Unfortunately the non-response rate in the SHIW is high rather high (Table 1) and previous studies show that non-response decision is not random. Cannari and D'Alessio (1992) analyzed the non-response bias to the SHIW using the second wave of the panel sub-sample (the first wave was interviewed in 1987, the second in 1989). Knowing the characteristics of who refused to respond in 1989, they expanded the results to the whole sample. This method assumes that the panel attrition bias presents the same causes as the non-response bias in the whole sample, which is debatable. They found that non-response characterizes households living in urban areas and those residing in the North. The participation rates decline as income rises and household size decreases, while the relationship with the age of the head of the households is ambiguous. D'Alessio and Faiella (2002) also showed that non-response behaviour is dependent on net financial wealth. They found this result using a supplementary sample of about 2,000 households, clients of a leading commercial bank and through a strict protocol devised to guarantee full protection of the interested clients' confidentiality, acquired data on financial assets both for respondent and non-respondent households. Although the sample can hardly be considered representative of the whole population and sub-samples size are not very large, individual with financial wealth larger than Lit 1 billion (about €0.5 million) have about half the respose rates of other groups.

year	response rate*
1987	64,3
1989	38,4
1991	33,2
1993	57,8
1994	56,9
1998	43,9

Table 1: Response rate in SHIW. Sources: Brandolini (1999) and Banca d'Italia (2000); * Ratio of responses to selected households net of ineligible units.

D'Alessio and Faiella (2002) tried to estimate non-response bias using different methodologies. For instance they used information about those who refused the interview on the first contact and accepted it on the second to infer about the characterstics of those who did not decide to participate. However, this is not a random sample of the non-respondent household, since decisions to participate to the interview after the first contact can depend on a large set of factors, and this methodology might introduce an additional bias which cannot be easily quantified. D'Alessio and Faiella (2002) used also alternative methodology reaching the conclusion that non-response behaviour is not random, and is more frequent among wealthier households. This implies that the poststratification techniques traditionally employed on a few known demographic characteristics of the population, such as sex and age, cannot fully account for the non-response bias.

Since the aim of the paper is to provide an estimate of the propensity of tax compliance by type of occupation, it is important that the characteristics of the individual in the SHIW data set are as close as possible to those of the population. The procedure of grossing-up is concerned with generating figures to cover the population being modelled from the data set under use. The procedure should adjust for differences between the sample data and the characteristics of the population to be modelled at the date of sampling.The grossing-up procedure is basically aimed at adjusting the data set to reflect differential non-response between different groups in the sample. It involves stratifying the sample, after the data have been collected, by some relevant characteristics, and applying known proportions. This procedure is also sometimes referred to as post-stratification (see for instance Atkinson and Micklewright (1983)).
The grossing-up procedure consists in assigning to each unit in a sample of dimension N a weight p_j, with $j=1,\ldots,N$, such that some chosen statistics of interest calculated on the weighted sample coincide with the population statistics. The procedure is trivial if we want to reconcile the sample with the population using only one discrete statistic, s_k with $k=1,\ldots,K$, such as family types or income ranges. In this case, we compute the probability of having the characteristic s_k in the

sample, say $P(s_k)$, and make it equal to the probability of having the same characteristic in the population, say $p(s_k)$. If the dimension of the sample and of the population are N and n respectively, then the grossing-up weight is $p_j=np(s_k)=NP(s_k)$, i.e. the size of the cell with characteristic s_k in the population divided by the size of the cell with characteristic s_k in the sample. If more variables are considered for the grossing-up procedure it should be necessary to consider the interactions between the different variables, i.e. consider the joint distribution of the control variables considered. However, this conflicts with available information from external sources, that in general, do not report the joint distribution of population variables but only the totals for each variable. For instance, it is generally possible to know the total number of single-parent families and the total number of self-employed in the population but not how many single-parent family have self-employment income. Hence, the conditions imposed on the weights p_j are far less stringent than in the "full information" case we would have if the joint distribution were known, and in general there are many possible sets of weights p_j achieving the desired adjustment. To choose among them Atkinson et al.(1988) suggest the requirement that given a data set of dimension N, with original sampling weights q_j, j=1, 2,…,N, the set of grossing-up weights p_j have the least deviation from original weights, q_j . The original weights could reflect the sampling procedure or be uniform. Both grossing-up and initial weights have to sum up to the population size: $\sum q_j = \sum p_j = n$. If original and sample weights sum up to the sample dimension, they first have to be multiplied by $n=N$. It is then common practice to impose the condition that the new weights minimize the distance from initial weights. In order to avoid negative weights, Atkinson et al. (1988) suggest minimizing a measure of distance derived from information theory (see for instance Cowell, 1980):

$$d(p,q) = \sum p_j \log\left(\frac{p_j}{q_j}\right)$$

As for the optimal number of control totals to be included, no result is currently available. Although it is more common to face the problem of not having enough external sources than to have too many, Sutherland (1989, p. 15) warns on the risk of increasing the variance of weights since the larger the number of control totals becomes, the smaller the number of observations in each "cell"(i.e. with each combination of characteristics being controlled for). Moreover, a particular set of grossing-up weights can be able to closely reflect the characteristics of the population as for some variables but not for others.

The SHIW data set is post-stratified using the variables sex, age class, area and dimension of the town of residence (Banca d'Italia, 2000, p. 40). However, it is not clearly stated what methodology was used and, for instance, which age classes were considered. Table 3 shows the population totals taken for ISTAT (Italian Institute of Statistics) as for a set of variables.

Using the weights provided in the SHIW data set, the differences between the grossed-up and actual figures are less than 0.2% for sex and area of residence (North-West (NW), North-East (NE), Center (C) and South (S)). As for the age classes, the difference between grossed-up and population figures is however more relevant: for instance, the grossed-up totals are under-estimated by 3.7% and over-estimated by 6.4% for the 18-30 and the over-65 years groups, respectively. Since the Bank of Italy does not make public the age groups considered, it could be possible that this difference is due to the different age groups used here. None the less, this shows a problem with grossed-up simulation: a redistributive policy in favor of the old age would imply an overstatement of its cost due to the over-sampling of this age group. These distortions could be even worse for other subsamples. For instance, using the same age groups divided in the 4 macro areas considered before, Table 3 shows that the SHIW grossed-up weights would over-represent the elderly living in the South (S) by about 25%. They would also induce an over-representation of the self-employed in the Center (C) and an under-representation the self-employed in the S (Table 3). Moreover, while the difference between the actual and the grossed-up total number of employed and self-employed is smaller than 1%, these figures hide a 29% over-representation of the self-employed in the C and an under-representation of self-employed in the NE and in the S by 13% and 21%, respectively. All these issues are of relevance whenever an analysis of income by population sub-groups is performed. For these reasons a set of alternative grossing-up weights were estimated using the same methodology as Atkinson et al. (1988) using control totals found in ISTAT(2004); CNEL (2004). Table 4 shows the results for six different weights: "weight 1" uses total population, by area, by sex, by age groups (below 18, between 19 and 30, between 31 and 65, over-65). Although the grossing-up methodology performs well for the variables considered, it does also have an effect on other variables. For instance, it has a positive effect on the over-65 living in the S, reducing its over-representation but it has a negative effect on the over-65 living in the C, increasing its under-representation. The "weight 2" improves on "weight 1" for grossing-up also on the age groups by area of residence. Although for some variables its effect is positive, reducing the discrepancy from actual totals, it is still rather unsatisfactory as for the number of employed and self-employed in different part of the countries. Since this is relevant for detecting the possibility of tax evasion/avoidance, some more grossing-up weights are estimated. Eventually, "weight 6" is chosen to replace the SHIW initial weights. It allows one to gross-up the sample to a population that is very close to the true population for a large number of relevant variables, including occupation by area of residence, education and sector of activity. However, as the last column of Table 4 shows, this weight is still unable to represent correctly the distribution of family by type: single households tend to be under-represented while couple with kids tend to be over-represented. It is chosen not to perform the grossing-up procedure also for type of families mainly because external data refer to families and SHIW refers uniquely to households. In choosing "weight 6" as final weight it was also considered the risk of increasing the variance of weights with respect to initial weights. The increased variance could come from two type of factors. First, in contrast to SHIW initial weights "weight 6" is not uniform within the household since the grossing-up procedure is performed at the individual level. Second, the larger the number of control totals the smaller the number of observations with each combination of characteristics being controlled (Sutherland, 1989). However, as Table 5 shows, the variance of "weight 6" is not larger than original SHIW weights.

	External sources	BI Weight	
	Total	Total	Diff
Males*	27,967,670	27,951,136	-0.06%
Females*	29,644,945	29,661,432	0.06%
Pop NW*	15,069,493	15,099,744	0.20%
Pop NE*	10,560,820	10,547,936	-0.12%
Pop C*	11,071,715	11,064,505	-0.07%
Pop S*	20,910,587	20,900,383	-0.05%
age≤18*	10,845,419	11,032,994	1.73%
18<age≤30*	9,987,651	9,619,324	-3.69%
30<age≤65*	27,218,646	26,787,452	-1.58%
age>65*	9,560,899	10,172,798	6.40%
age≤18NW*	2,409,663	2,497,552	3.65%
age≤18NE*	1,687,699	1,853,786	9.84%
age≤18C*	1,873,809	2,073,762	10.67%
age≤18S*	4,874,248	4,607,894	-5.46%
18<age≤30NW*	2,498,184	2,411,373	-3.47%
18<age≤30 NE*	1,766,221	1,630,855	-7.66%
18<age≤30 C*	1,824,075	1,988,102	8.99%
18<age≤30 S*	3,899,171	3,588,994	-7.95%
30<age≤65 NW*	7,509,728	7,523,230	0.18%
30<age≤65 NE*	5,174,474	5,070,504	-2.01%
30<age≤65 C*	5,368,887	5,191,858	-3.30%
30<age≤65 S*	9,165,557	9,001,860	-1.79%
age>65 NW*	2,651,918	2,667,589	0.59%
age>65 NE*	1,932,426	1,992,791	3.12%
age>65 C*	2,004,944	1,810,783	-9.68%
age>65 S*	2,971,611	3,701,635	24.57%
employed**	14,549,000	14,530,169	-0.13%
self-employed**	5,886,000	5,852,953	-0.56%
employed NO**	4,470,000	4,345,113	-2.79%
employed NE**	3,104,000	3,199,310	3.07%
employed C**	2,911,000	2,821,364	-3.08%
employed S**	4,086,000	4,164,382	1.92%
self-empl NO**	1,643,000	1,793,760	9.18%
self-empl NE**	1,330,000	1,156,244	-13.06%
self-empl C**	1,184,000	1,532,649	29.45%
self-empl S**	1,730,000	1,370,300	-20.79%
Elementary schooling*	16,104,000	15,625,930	-2.97%
Compulsory schooling*	16,118,000	13,975,447	-13.29%
High School degree*	13,365,000	15,402,757	15.25%
Laurea*	3,066,000	3,641,053	18.76%
Agriculture**	1,201,000	1,038,245	-13.55%
Industry**	6,730,000	6,548,547	-2.70%
Services**	12,504,000	12,796,330	2.34%
Single*	4,982,000	4,380,481	-12.07%
Single parent*	1,655,000	1,666,809	0.71%
Couple no kids*	3,828,000	4,373,753	14.26%
Couple w/ kids*	9,410,000	9,978,556	6.04%
Others*	1,440,000	773,930	-46.25%
All families*	21,315,000	21,173,529	-0.66%

Table 3: Original and grossing-up weights. External sources: *ISTAT (2004) and **CNEL (2004).

	External sources	Weight 1		Weight2		Weight3		Weight4		Weight5		Weight6	
	Total	Total	Diff	Total	Diff	Total	Diff	Total	Diff	Total	Diff	Total	Diff
Males*	27,967,670	27,967,738	0.00%	27,967,745	0.00%	27,967,768	0.00%	27,967,691	0.00%	27,967,666	0.00%	27,967,812	0.00%
Females*	29,644,945	29,644,996	0.00%	29,645,024	0.00%	29,644,921	0.00%	29,645,047	0.00%	29,645,027	0.00%	29,645,007	0.00%
Pop NW*	15,069,493	15,069,523	0.00%	15,069,538	0.00%	15,069,537	0.00%	15,069,535	0.00%	15,069,524	0.00%	15,069,552	0.00%
Pop NE*	10,560,820	10,560,844	0.00%	10,560,808	0.00%	10,560,852	0.00%	10,560,850	0.00%	10,560,811	0.00%	10,560,825	0.00%
Pop C*	11,071,715	11,071,708	0.00%	11,071,783	0.00%	11,071,708	0.00%	11,071,748	0.00%	11,071,755	0.00%	11,071,777	0.00%
Pop S*	20,910,587	20,910,659	0.00%	20,910,640	0.00%	20,910,592	0.00%	20,910,605	0.00%	20,910,603	0.00%	20,910,665	0.00%
age≤18*	10,845,419	10,845,442	0.00%	10,845,466	0.00%	10,845,422	0.00%	10,845,437	0.00%	10,845,455	0.00%	10,845,487	0.00%
18<age≤30*	9,987,651	9,987,683	0.00%	9,987,658	0.00%	9,987,698	0.00%	9,987,679	0.00%	9,987,642	0.00%	9,987,667	0.00%
30<age≤65*	27,218,646	27,218,712	0.00%	27,218,727	0.00%	27,218,684	0.00%	27,218,670	0.00%	27,218,696	0.00%	27,218,729	0.00%
age>65*	9,560,899	9,560,897	0.00%	9,560,918	0.00%	9,560,885	0.00%	9,560,952	0.00%	9,560,900	0.00%	9,560,936	0.00%
age≤18NW*	2,409,663	2,448,122	1.60%	2,409,678	0.00%	2,452,333	1.77%	2,462,053	2.17%	2,464,446	2.27%	2,409,685	0.00%
age≤18NE*	1,687,699	1,825,501	8.17%	1,687,702	0.00%	1,829,320	8.39%	1,813,836	7.47%	1,816,658	7.64%	1,687,714	0.00%
age≤18C*	1,873,809	2,036,606	8.69%	1,873,838	0.00%	2,040,402	8.89%	2,122,875	13.29%	2,146,916	14.57%	1,873,829	0.00%
age≤18S*	4,874,248	4,535,213	-6.96%	4,874,248	0.00%	4,523,367	-7.20%	4,446,673	-8.77%	4,417,435	-9.37%	4,874,259	0.00%
18<age≤30NW*	2,498,184	2,496,925	-0.05%	2,498,198	0.00%	2,485,397	-0.51%	2,498,413	0.01%	2,508,562	0.42%	2,498,199	0.00%
18<age≤30 NE*	1,766,221	1,696,552	-3.94%	1,766,211	0.00%	1,685,816	-4.55%	1,680,691	-4.84%	1,673,535	-5.25%	1,766,212	0.00%
18<age≤30 C*	1,824,075	2,062,713	13.08%	1,824,076	0.00%	2,064,014	13.15%	2,052,503	12.52%	2,036,362	11.64%	1,824,073	0.00%
18<age≤30 S*	3,899,171	3,731,493	-4.30%	3,899,173	0.00%	3,752,471	-3.76%	3,756,072	-3.67%	3,769,183	-3.33%	3,899,183	0.00%
30<age≤65 NW*	7,509,728	7,624,243	1.52%	7,509,742	0.00%	7,628,840	1.59%	7,605,731	1.28%	7,607,615	1.30%	7,509,730	0.00%
30<age≤65 NE*	5,174,474	5,162,376	-0.23%	5,174,474	0.00%	5,164,466	-0.19%	5,194,626	0.39%	5,205,307	0.60%	5,174,472	0.00%
30<age≤65 C*	5,368,887	5,271,826	-1.81%	5,368,918	0.00%	5,265,679	-1.92%	5,136,223	-4.33%	5,117,690	-4.68%	5,368,921	0.00%
30<age≤65 S*	9,165,557	9,160,267	-0.06%	9,165,593	0.00%	9,159,699	-0.06%	9,282,090	1.27%	9,288,084	1.34%	9,165,606	0.00%
age>65 NW*	2,651,918	2,500,233	-5.72%	2,651,920	0.00%	2,502,967	-5.62%	2,503,338	-5.60%	2,488,901	-6.15%	2,651,938	0.00%
age>65 NE*	1,932,426	1,876,415	-2.90%	1,932,421	0.00%	1,881,250	-2.65%	1,871,697	-3.14%	1,865,311	-3.47%	1,932,427	0.00%
age>65 C*	2,004,944	1,700,563	-15.18%	2,004,951	0.00%	1,701,613	-15.13%	1,760,147	-12.21%	1,770,787	-11.68%	2,004,954	0.00%
age>65 S*	2,971,611	3,483,686	17.23%	2,971,626	0.00%	3,475,055	16.94%	3,425,770	15.28%	3,435,901	15.62%	2,971,617	0.00%
employed**	14,549,000	14,832,997	1.95%	14,830,481	1.93%	14,549,021	0.00%	14,549,021	0.00%	14,549,022	0.00%	14,549,025	0.00%
self-employed**	5,886,000	5,951,129	1.11%	5,942,476	0.96%	5,886,031	0.00%	5,885,996	0.00%	5,885,999	0.00%	5,886,023	0.00%
employed NO**	4,470,000	4,428,138	-0.94%	4,381,285	-1.98%	4,346,883	-2.75%	4,470,026	0.00%	4,470,001	0.00%	4,470,008	0.00%
employed NE**	3,104,000	3,276,169	5.55%	3,317,881	6.89%	3,218,263	3.68%	3,103,998	0.00%	3,103,985	0.00%	3,103,999	0.00%
employed C**	2,911,000	2,877,905	-1.14%	2,838,694	-2.48%	2,824,913	-2.96%	2,911,003	0.00%	2,911,012	0.00%	2,911,011	0.00%
employed S**	4,086,000	4,250,785	4.03%	4,292,621	5.06%	4,158,962	1.79%	4,063,994	-0.54%	4,064,024	-0.54%	4,064,007	-0.54%
self-empl NO**	1,643,000	1,817,118	10.60%	1,802,766	9.72%	1,798,636	9.47%	1,642,995	0.00%	1,642,994	0.00%	1,643,006	0.00%
self-empl NE**	1,330,000	1,178,261	-11.41%	1,190,253	-10.51%	1,167,382	-12.23%	1,330,003	0.00%	1,330,004	0.00%	1,329,990	0.00%
self-empl C**	1,184,000	1,560,119	31.77%	1,548,420	30.78%	1,543,659	30.38%	1,184,001	0.00%	1,184,002	0.00%	1,184,014	0.00%
self-empl S**	1,730,000	1,395,631	-19.33%	1,401,037	-19.02%	1,376,354	-20.44%	1,728,997	-0.06%	1,728,999	-0.06%	1,729,013	-0.06%
Elementary schooling*	16,104,000	15,303,360	-4.97%	15,235,698	-5.39%	15,381,891	-4.48%	15,387,753	-4.45%	16,104,016	0.00%	16,104,072	0.00%
Compulsory schooling*	16,118,000	14,110,613	-12.45%	14,156,361	-12.17%	14,100,825	-12.52%	14,121,594	-12.39%	16,118,021	0.00%	16,118,041	0.00%
High School degree*	13,365,000	15,692,853	17.42%	15,725,012	17.66%	15,646,311	17.07%	15,619,639	16.87%	13,365,006	0.00%	13,365,007	0.00%
Laurea*	3,066,000	3,691,111	20.39%	3,687,272	20.26%	3,663,811	19.50%	3,661,898	19.44%	3,065,999	0.00%	3,066,023	0.00%
Agriculture**	1,201,000	1,058,337	-11.88%	1,064,699	-11.35%	1,039,454	-13.45%	1,055,137	-12.15%	1,200,997	0.00%	1,201,005	0.00%
Industry**	6,730,000	6,686,566	-0.65%	6,684,699	-0.67%	6,579,136	-2.24%	6,574,907	-2.30%	6,730,011	0.00%	6,730,028	0.00%
Services**	12,504,000	13,039,223	4.28%	13,023,559	4.16%	12,816,462	2.50%	12,804,973	2.41%	12,504,013	0.00%	12,504,015	0.00%
Single*	4,982,000	4,245,869	-14.78%	4,251,030	-14.67%	4,240,640	-14.88%	4,226,747	-15.16%	4,230,030	-15.09%	4,236,991	-14.95%
Single parent*	1,655,000	1,676,363	1.29%	1,664,537	0.58%	1,674,495	1.18%	1,669,811	0.89%	1,685,693	1.85%	1,672,088	1.03%
Couple no kids*	3,828,000	4,289,382	12.05%	4,296,591	12.24%	4,297,968	12.28%	4,290,829	12.09%	4,278,283	11.76%	4,289,241	12.05%
Couple w/ kids*	9,410,000	10,061,245	6.92%	10,052,744	6.83%	10,059,334	6.90%	10,069,620	7.01%	10,056,183	6.87%	10,047,093	6.77%
Others*	1,440,000	760,855	-47.16%	753,073	-47.70%	760,403	-47.19%	762,475	-47.05%	762,409	-47.05%	754,947	-47.57%
All families*	21,315,000	21,033,714	-1.32%	21,017,975	-1.39%	21,032,840	-1.32%	21,019,482	-1.39%	21,012,598	-1.42%	21,000,360	-1.48%

Table 4: Grossed-up variables using Banca d'Italia (2000) grossing-up weights compared with population totals. *External source: ISTAT (2004); **CNEL (2004).

weight	obs	mean	std.dev.	min	max
SHIW	20901	2756,453	2688,614	228,1136	28395,24
weight 1	20901	2756,453	2672,33	232,074	28755
weight 2	20901	2756,453	2669,014	232,642	28236
weight 3	20901	2756,453	2671,421	228,981	28569,5
weight 4	20901	2756,453	2669,172	220,594	27490,8
weight 5	20901	2756,453	2760,695	186,943	33526,2
weight 6	20901	2756,453	2759,995	183,083	33711,1

Table 5: Summary statistics for initial SHIW and final grossing-up weights.

4 Estimating tax evasion

The first difficulty that authors have to face in measuring tax evasion is how to define it. Tax evasion is sometimes referred to as income produced in the underground economy, however this is not completely correct. Table 6 provides a taxonomy of what are underground activities distinguishing between illegal and legal activities, between monetary and non-monetary transactions. In this paper illegal activities are not considered. In fact the methodology adopted here is a direct methodology whose basic assumption is that an income receiver who decides to evade tax payment will in part or in total under-report her taxable income tax authorities and declare the true income, or at least closer approximation to the true income, to an interviewer who grants anonymity. Survey-based data tend to grant anonymity to increase the probability of participation in the survey and of truthful declarations. Hence, the comparison of income distribution using the tax records and survey-based data sets allows one to have a picture of tax evasion behaviour, possibly across different income levels and different type of incomes. Criminal or illegal economy (tax avoidance and evasion due illegal activities such as drug trafficking or unauthorised medical practice) is not included since we believe that those incurring in such activities are very unlikely to accept the interview or respond truthfully even to an anonymous interviewer.

Type of Activity	Monetary Transactions		Non Monetary Transactions	
Illegal Activities	Trade with stolen goods; drug dealing and manufacturing; prostitution; gambling; smuggling and fraud		Barter of drugs, stolen goods, smuggling etc. Produce or growing drugs for own use. Theft for own use.	
	Tax Evasion	**Tax Avoidance**	**Tax Evasion**	**Tax Avoidance**
Legal Activities	Unreported income from self-employment; Wages, salaries and assets from	Employee discounts, fringe benefits	Barter of legal services and goods	All do-it-yourself work and neighbor help

Table 6: A Taxonomy of Types of Underground Economic Activities. Source Schneider (2000b)

In this paper on Italian tax evasion we use the 1998 Survey of Household Income and Wealth dataset (SHIW), produced by the Bank of Italy (BI) through anonimous interview of a random sample from the Italian household population. The 1998 SHIW data set is then compared with the tables of the Ministry of Finance (MF) (Ministero delle Finance, 2004) on tax returns for incomes produced in 1998.

Although this methodology is widely used in statistical officies and was already exploited by other authors before (recall Section 2), it presents a bunch of complications, which is worth pointing out. The sampling design of the SHIW data set is meant to provide a representative sample of the household population, in the MF tables instead we only have information on individual incomes since personal income tax is on individual base. SHIW data are detailed at the micro unit, while MF tables report information by income classes. SHIW collects information about a representative sample of the population, MF tables about the whole population: a discrepancy might also come from sampling error. In the SHIW data set we can connect individual characteristics to each income, in MF tables only aggregate data are reported and division of the population among different occupation is feasible to the cost of some approximations. SHIW data are based on recall questions and are known to be highly unreliable as for some type of incomes (in particular capital income), MF tables are developed from tax forms, hence collecting detailed information on all types of declared taxable incomes. The SHIW data collect information on disposable income only, and not on amount of taxes paid. Finally, SHIW data are likely to present measurement error due to recording mistakes of the interviewer, imprecise answers of the interviewed household who are not required to provide evidence of their incomes; MF data instead, come directly from tax forms and they might include mainly tax-payer mistakes in tax form filling and tax form data elaboration mistakes.

Notwithstanding these limitations we believe that such a comparison is informative, though it presents wide margins of improvement mainly depending on data quality and availability. The exercise we perform here is similar to that of Marenzi (1996) and it can be seen as an update to 1998 of that paper. However, our work differs from Marenzi (1996) for two main reasons: (a) we carefully consider the issue of grossing-up, (b) we analyze employment and self-employment income only. As described in Section 3, the sampling weights provided by the BI are far from providing a reliable picture of the underlying population especially if particular sub-samples are considered. The Atkinson et al. (1988) procedure we adopted is meant to reduce such biases in comparing incomes by types. The focus on employment and self-employment income was decided since capital and building and estate income is very noisy in SHIW data set (for instance, see Brandolini (1999) referred to 1995 SHIW) and differences in pension income might reasonably come only from measurement error rather than to explicit underreporting behaviour since the probability of being caught evading tax on pension income is nearly one as the pension system is mainly managed by the state.

According to the methodology adopted, the SHIW disposable income is expected to be higher than MF data. This difference can be considered as the sum of underground economy (tax avoidance and evasion concerning legal activities) and of informal economy (individual activity with low level of organization, based on individual and familiar relationship, such as baby sitting, domestic cleaning, etc.). In what follows we will briefly refer to is as tax evasion. Criminal or illegal economy (tax avoidance and evasion due illegal activities such as drug trafficking or unauthorised medical practice) is reasonably not included since we believe that those incurring in such activities are very unlikely to accept the interview or respond truthfully even to an anonymous interviewer.

Table 7 shows that employment income is underdeclared in bottom deciles. The first income deciles of employment income present a non negligible rate of tax evasion. As for the first decile, the actual income is underdeclared by about 55%. Then, employment income evasion decreases regularly and is smaller than 5% after the median. There are might be two main reasons for such a pattern. First, informal economy with low level of organization, based on individual and familiar relationship, is likely to be wide spread at low level of incomes. Second, it is well-known that SHIW data set does not present a satisfactory representation of the bottom tail of the income distribution, hence it might be that the income which is larger than the 10% of all employment incomes in the SHIW data set is actually larger of a larger share of all employment income in the population.

Self-employment income presents instead a clearly different pattern of tax evasion. The amount of non-declared self-employment income ranges between 27% and 9%, being rather stable between the 3rd and the 8th decile. In the 1st quantile on average 27% of income is evaded though in the following decile income is underdeclared by 6% only. The picture that emerges from Table 7 is that tax evasion is present in both employment and self-employment income and that it is mainly concentrated in lower deciles for employment incomes and uniformly distributed for self-employment income. The share of non-declared income in self-employment income is approximately 17%.

Decile	Employees			Self-employed		
	BI	MF	Evasion (ei)	BI	MF	Evasion (ei)
1	9000	4036.52	55%	5896	4313.50	27%
2	15162	10843.12	28%	10000	9413.79	6%
3	19000	15362.80	19%	14000	12049.84	14%
4	22000	19692.04	10%	18000	14901.60	17%
5	24000	22698.42	5%	22500	18600.20	17%
6	26000	26035.32	0%	25000	20579.73	18%
7	30000	29226.10	3%	30777	25422.41	17%
8	35000	33470.00	4%	36000	30398.03	16%
9	40000	39537.50	1%	50000	45305.35	9%

Table 7: Difference of individual income declared to the Bank of Italy (BI) and to the Ministry of Finance (MF), by deciles in Lit '000 (Lit 1936.27=€1).

Of course some caveats should be mentioned. This analysis shows a picture that is roughly comparable to other previous analysis. However, some bias in these estimations might come from various sources and mainly from measurement errors. In fact the SHIW questionnaire asks interviewees a rather complicated question to recall their year before income. For employee it is asked their 1998 income net of taxes, social contributions, severance pay, withholding tax and social security contributions but including additional monthly salary, bonuses, special emoluments and other compensations. For self-employed earnings net of taxes are asked, which are computed as revenues from sales of goods and services net of VAT plus other revenues minus ordinary maintenance expenditures, purchase of raw material and goods, employee compensation, current expenses, rent of premises, taxes and other expenditures. It is likely that such a calculation might present a high degree of approximation. Since there is no way to properly account for such a measurement error, we assume that at this level of disaggregation it might be negligible. However it is likely to significantly increase the lower is the reliability of income variables and the thinner is the break-down of the sample. As for the MF tables we refer to, some level of approximation is also involved. MF tables are not presented by deciles of income but by income classes and deciles have been obtained by considering the number of people in each income class. This procedure clearly assumes that the distribution within each income class is uniform, however it is a smaller approximation than using the nearest income class.

5 Tax evasion and inequality

The results presented in the Section 4 rise a set of concerns about equity and distorsion effects of taxation. It was shown that probability of evading taxation is not evenly distributed across different income levels and across different types of incomes. We do not consider the case of individuals belonging to the same income quantile and equal type of income and deciding different tax compliance behaviour. However, even with this simplifying assumption these different probability of tax evasion might alter the distribution of income and measures of poverty and income inequality. They might vastly reduce the amount of tax revenues. They might induce employees to move to a self-employed position to be able to reduce their tax burden. They might induce people at lower levels of income not to enter the official labour market and to remain employed in the hidden economy reducing the participation to the labour market or refusing to move into employment increasing unemployment rate.

Here we focus on effects of tax evasion on income inequality. The analysis is performed creating some counterfactuals, where it is assumed that tax-payers declare what is their true income, the latter assumed to be as the one declared in the SHIW. Such counterfactuals are not created multiplying individual incomes by the evasion coefficients in Table 7 because it would involve major re-rankings around each income decile. For instance, if we multiplied by 37% the income of the individual whose self-employment income is equal to the first decile and by 6% that of the individual whose self-employment income is just above the first decile it is likely that the latter would move the the first decile and viceversa. A piece-linear evasion function for both employed and self-employed income is applied instead. Let Y_i be the SHIW after-tax income, E_i be the evaded income, e_i the marginal evasion rate of individual i, B_j the j-th income decile, with $B_0=0$,

$$E_i = \sum_{j=1}^{9} Z_j (B_j - B_{j-1}) e_j + I_j (Y_i - B_{j-1}) e_j$$

where

$$I_j = \begin{cases} 1 & if \quad B_{j-1} < Y_i \le B_j \\ 0 & if \quad o.w. \end{cases}$$

and

$$Z_j = \begin{cases} 1 & if \quad B_{j-1} < Y_i \\ 0 & if \quad o.w. \end{cases}$$

The marginal evasion rates, e_i, are taken from Table 7. For instance the imputation of tax evasion for employment income can be seen in Figure 1.

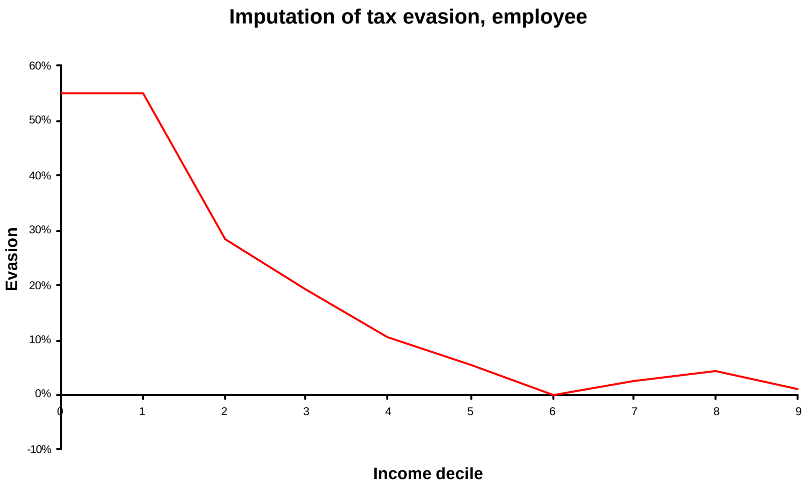

Figure 1: the evasion function for employment income

As SHIW records only disposable income after all taxes and social contributions (AT), a microsimulation model is used to simulate before-tax income (BT). The TABEITA98 model used is a static microsimulation model which simulates IRPEF and "imposte sostitutive" on 1998 SHIW (for details about the model see Fiorio, 2004). Analysis of inequality is performed using Lorenz curves and some Generalized Entropy indices, with parameter $a=0,1,2$ in order to have an idea of the effects of the simulation along income range[1]. The simulation of tax evasion as describe above does produce large changes in both BT and AT income. Looking at all taxpayers, the GE indices change between 5.9% and 10.9%. It is worth noting that main changes comes from simulated evasion of employment income and, especially in the bottom part of the distribution, as shown by the *GE(0)* index (Table 8). This is clearly due to the fact that tax evasion simulation highly increases bottom decile employment income while the simulation of tax evasion in self-employment income is more evenly spread across different deciles.

Tipology of taxpayer	Income considered	GE(0)		GE(1)		GE(2)	
		Value	Var.	Value	Var.	Value	Var.
All taxpayers	Declared BT income	0,7326		0,5497		1,2578	
	Disposable BT income	0,6891	-5,9%	0,5109	-7,1%	1,1436	-9,1%
	Declared AT income	0,6201		0,4210		0,7449	
	Disposable AT income	0,5836	-5,9%	0,3863	-8,2%	0,6635	-10,9%
Taxpayers with work income	Declared BT income	0,4414		0,4462		1,0746	
	Disposable BT income	0,3442	-22,0%	0,3832	-14,1%	0,9282	-13,6%
	Declared AT income	0,3439		0,3252		0,6276	
	Disposable AT income	0,2556	-25,7%	0,2652	-18,4%	0,5166	-17,7%
Taxpayers with employment income	Declared BT income	0,3470		0,2743		0,3601	
	Disposable BT income	0,2369	-31,7%	0,2142	-21,9%	0,2937	-18,4%
	Declared AT income	0,2795		0,2114		0,2420	
	Disposable AT income	0,1783	-36,2%	0,1529	-27,6%	0,1835	-24,2%
Taxpayers with self-employment income	Declared BT income	0,6088		0,6615		1,6213	
	Disposable BT income	0,5446	-10,5%	0,5973	-9,7%	1,4210	-12,4%
	Declared AT income	0,4697		0,4976		1,0463	
	Disposable AT income	0,4121	-12,3%	0,4344	-12,7%	0,8737	-16,5%

Table 8: Simulated change in inequality indices due to tax evasion

These results are also confirmed by Lorenz curves (Figures X1-X4).

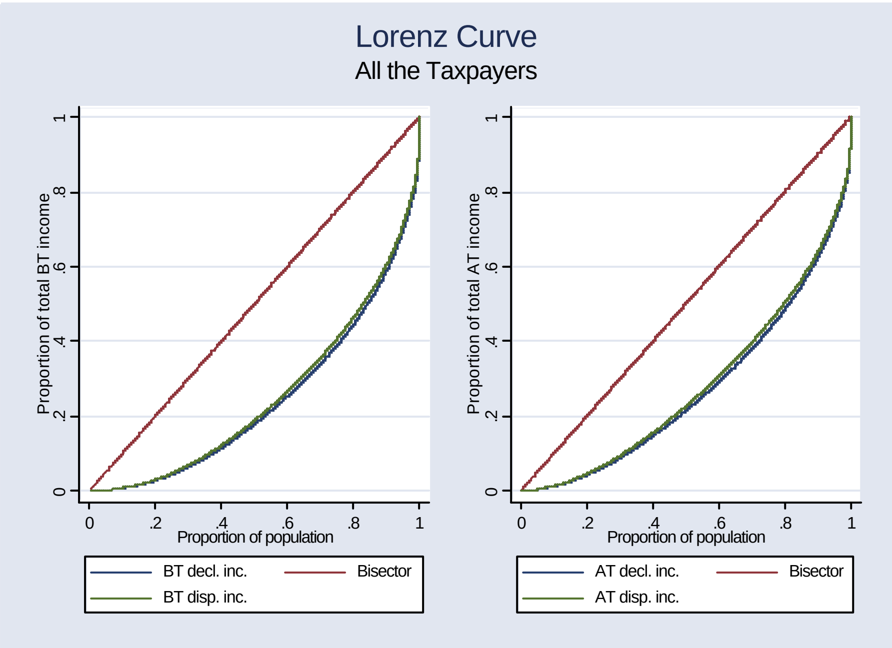

Figure 2

[1] The smaller is the coefficient a the more sensitive is the generalized entropy index to changes in the bottom of the distribution, and viceversa (see Cowell, 1995).

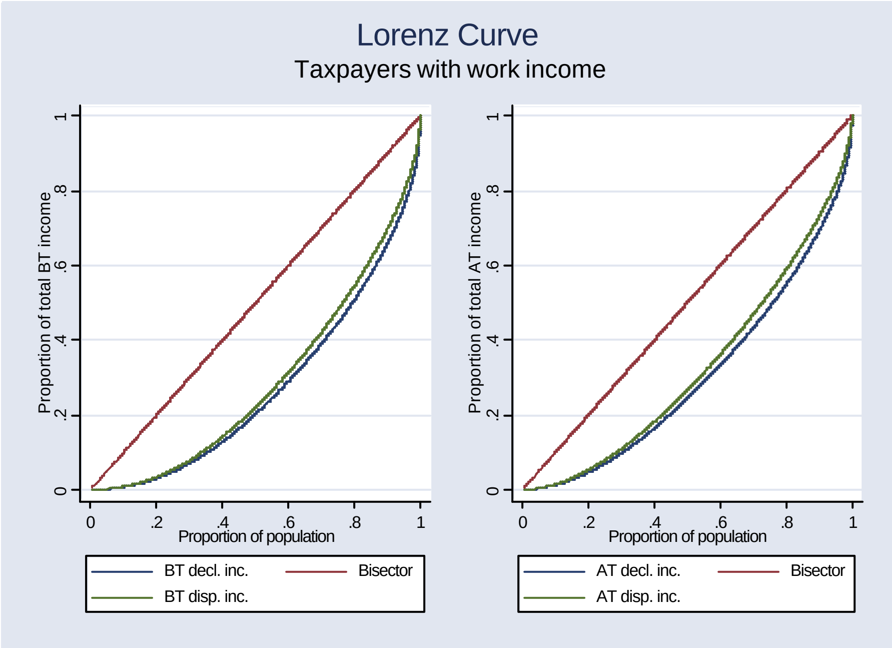

Figure 3

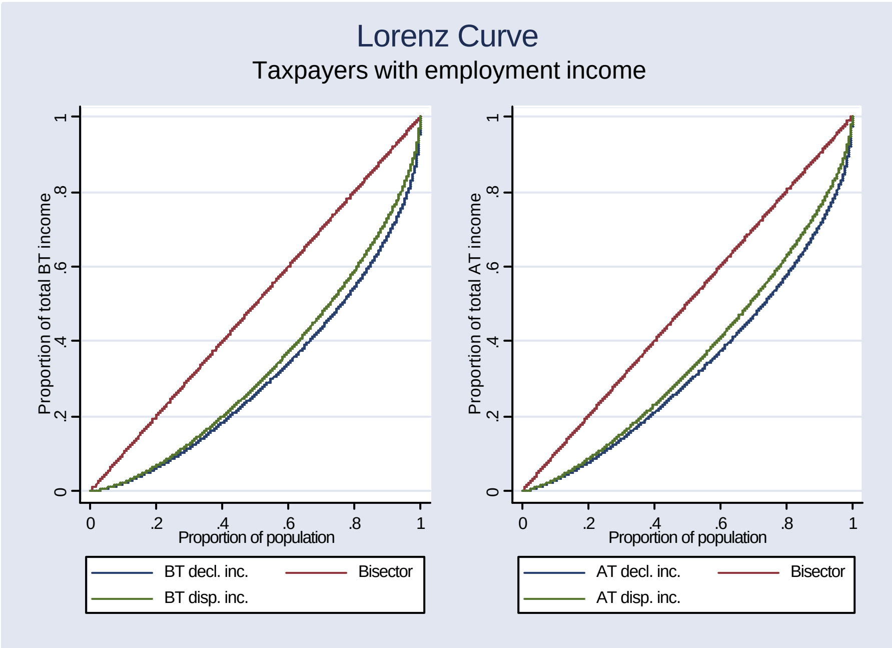

Figure 4

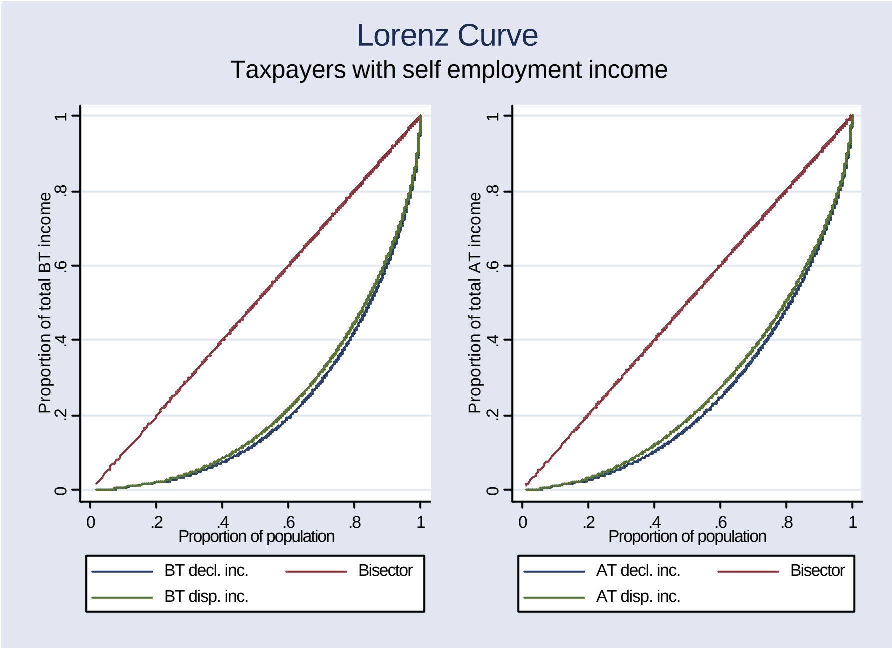

Figure 5

6 Discussion and conclusions

This paper updates to 1998 the estimation of tax evasion in Italy using a direct methodology, which is based on the assumption that an individual who decides to partly or completely hide income to tax authorities is likely to be more truthful with an institution that grants anonymity. The 1998 SHIW and the analysis of tax forms are then compared. However, it is highlighted that 1998 SHIW has some problems of representativeness of the true population. Using the sample weights provided in the data set some statistics, such as the number of self-employment in the Center or the over 65 are seriously biased upward, some others, such as self-employed in the South, seriously biased downward.

In order to reduce such a problem a procedure of grossing-up the sample to known totals is performed prior to any tax evasion estimation. The results found are comparable to that of previous studies. It is found that tax evasion is a phenomenon that affects both employment and self-employment income. However, it is large only for bottom deciles of the employment distribution and negligible for larger ones, probably because of part-time or irregular occupations. As for self-employment income, instead, chances of tax evasion is more evenly spread across all income levels and amount to about 17% on average. This difference of tax evasion among employment and self-employment income is likely to introduce some distortion as for the individual decision to work as an employee or a self-employed.

The simulation of tax evasion effects on income inequality shows that had all individuals declared their true income to tax authorities, overall inequality would have been reduced by 6-11%, depending on the inequality index used. The reduction of inequality would have been larger for employment income as evasion imputation would imply a large increase of bottom deciles with no large change of the others.

However some caveats should be put forward. First, it should be noticed the importance of the assumption that tax evaders trust an institution that collects household survey data granting anonymity and decide to declare to its interviewers an income that is closer to true income than what stated in tax forms. For this reason, tax evasion estimation provided here are likely to be conservative. Second, sample selection is likely to be an issue. Although the grossing-up procedure undertaken in this paper is aimed at reducing under-sampling of relevant population subgroups, it is likely to remain a problem especially since the survey presents a response rate lower than 50%. Third, the tax form data provided by the Ministry of Finance are at a high level of aggregation and their use needs a large amount of approximation. Finally, the focus of the paper has been on work income, because SHIW data for capital and estate and building income is less reliable. It is likely that evasion of tax on capital, estate and building income would have an inequality increasing effect since it is likely to benefit more higher incomes.

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