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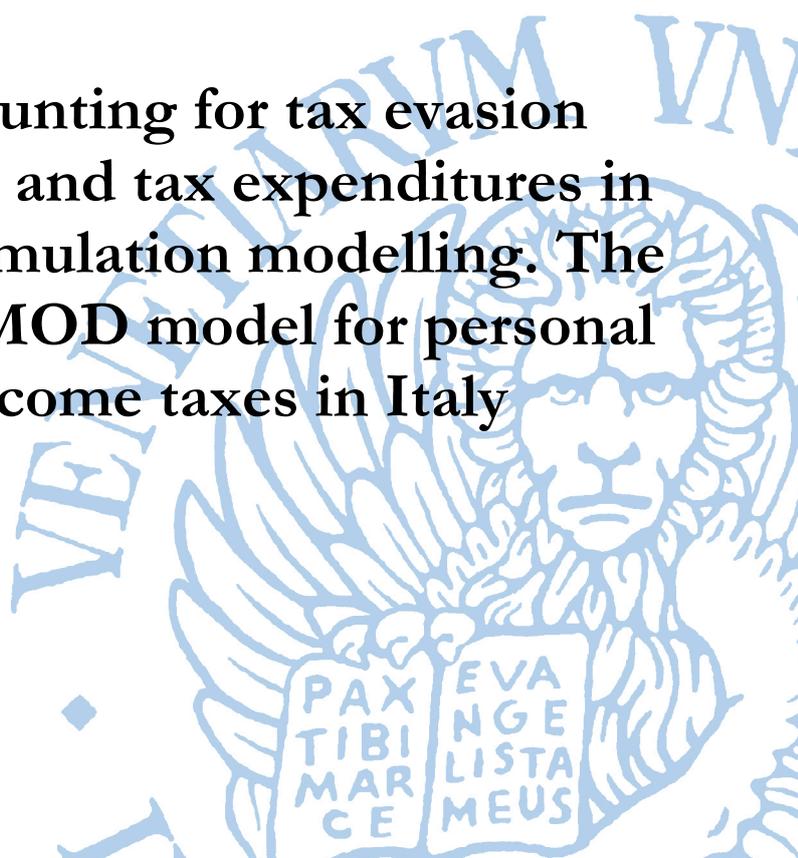
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Working Paper

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# Accounting for tax evasion profiles and tax expenditures in microsimulation modelling. The BETAMOD model for personal income taxes in Italy

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## Abstract

The paper presents the main characteristics of BETAMOD, a static microsimulation model that reproduces the Italian personal income tax (IRPEF), as well as local income taxes, namely the regional and municipal additional income taxes, building on a detailed reconstruction of tax legislation. With respect to the vast majority of existing tax microsimulation models, the peculiarities of BETAMOD concern two aspects: the inclusion of a detailed set of tax expenditures, and the estimation of individual-specific tax evasion rates, which account for the total individual income level, its composition in terms of income sources, and the geographical area of residence.

**KeyWords:** Tax-benefit microsimulation, tax evasion, tax expenditures, SILC, Italy

**JEL Codes:** C15, C63, H20, H24, H26, H31

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## 1. INTRODUCTION

The increasing complexity of fiscal challenges requires appropriate instruments to evaluate the revenue effects and the distributional consequences of specific policies. Microsimulation models, based on representative sample of individuals or households, take into account the heterogeneity of individual behavior, reproduce a part or the whole tax and benefit system of a country, regions or group of States (Sutherland and Figari, 2013) and are able to identify the winners and the losers of tax/transfer policies. Microsimulation models have become in many countries a standard tool for the design and the evaluation of public policies (see, among others, Bourguignon and Spadaro, 2006; Mitton, Sutherland and Weeks, 2000).

This paper presents a new microsimulation model, called BETAMOD, for Italian personal income tax (IRPEF), as well as local income taxes, namely the regional and municipal additional income taxes.

BETAMOD improves on existing models<sup>1</sup> in two ways: first, by estimating a distribution of individual tax evasion rates, based on total individual income level, its composition in terms of sources, and geographical area; second, by accounting for a detailed set of tax allowances, which are currently the object of fiscal policy reforms debate, at the national and international level (e.g. Tyson, 2014). For different reasons, the two aspects are relevant in the Italian institutional setting and therefore deserve particular attentions.

Tax evasion in Italy is extremely high and various political leaders as well as a significant share of the public opinion seem to justify tax evaders using the argument that the tax rates are too high and the tax schedule too progressive. The answer to the above question depends on the redistributive effects of tax evasion and, more specifically, on the distinct effects that tax evasion may have on progressivity (vertical effect) versus horizontal equity and re-ranking (Aronson and Lambert, 1994). With respect to other Italian models, where tax evasion rates are assumed to be constant within population subgroups (e.g. by income source type, by income classes), BETAMOD, assigns a tax evasion rate to each individual. This allows to evaluate more accurately how tax evasion may alter the redistributive effect of personal income taxation, and to measure the horizontal, vertical and re-ranking effects, each of which is possibly altered by tax evasion.

Over the last decade, tax expenditures in Italy have increased as a share of GDP. The Italian Ministry of Economy and Finance identifies 720 measures of tax expenditures that, in percent of

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<sup>1</sup> In the past decade several microsimulation models were developed in Italy. Models belong to the same type of BETAMOD are: the Siena microsimulation model (SM2) for net-gross conversion of EU-SILC income variables (Betti *et al.* 2011); the MAPP model for studying the effects of taxes and transfers (in cash and in kind) on the level of poverty and inequality (Baldini *et al.*, 2011); the TABETTA model that reproduces the Italian personal income tax (Ceriani *et al.*, 2013), and the microsimulation model developed by Pellegrino *et al.* (2011) for the analysis of housing taxation.

GDP, account for about 10.66 (MEF, 2011). Among them, the individual income tax expenditures are the largest (4.84% of GDP). Because of the entailed reduction in tax revenues, and the induced distortions in taxpayers' behavior, there is an increasing debate on the use of tax expenditures as alternative to direct expenditures (see, Burman, 2003; Burman *et al.*, 2008; Poterba, 2011). Compared to current microsimulation models for Italy, BETAMOD includes all kind of individual income tax expenditures and allows us to estimate the distributional effects of all tax expenditures simultaneously and of specific tax reliefs or categories of expenditure.

The paper is organized as follows. Section 2 describes the data set and the preliminary data adjustments and imputations required to simulate accurately the Italian personal income taxes. Section 3 illustrates, in details, the process of constructing BETAMOD, focusing in particular on its innovative aspects. Section 4 tests the robustness of the model by comparing the baseline simulation of personal income tax and local income taxes with official figures provided by tax returns data. Finally, Section 5 provides novel distributional evidences on tax evasion and on its profile, as well as on individuals' re-ranking between income classes resulting from it<sup>2</sup>.

## 2. THE MICRO DATABASE AND RELATED IMPUTATIONS

BETAMOD runs on the Italian national version of the Survey of Income and Living Conditions (IT-SILC), which represents, with a few exceptions, the micro-database currently chosen by most tax-benefit microsimulation models for Italy<sup>3</sup>. With respect to the alternative Survey on Households Income and Wealth (SHIW), IT-SILC takes the advantage of a more generous sample size (19,399 households in IT-SILC versus 7,951 households in SHIW), allowing to conduct analyses by geographical area sample; the drawback of this choice is the lack of information on household's assets and tax-relevant expenditures.

We use the cross-sectional component of IT-SILC 2011, which features a considerably larger sample size than the rotating longitudinal component. The interview is structured into an household level questionnaire, collecting information on household composition, accommodation, housing costs, and economic circumstances (including savings, debts, receipt of family-related and means-tested benefits and children's incomes); and an individual level questionnaire, which is administered to all household members aged 16 years old or above. In the

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<sup>2</sup> Further material is provided in three Appendices. Appendix A describes the statistical matching between the IT-SILC dataset and the Bank of Italy's Survey on Households Income and Wealth (SHIW); Appendix B illustrates the methodology used for the estimation of individual tax evasion rates, and Appendix C shows the incidence of tax reliefs on reported income.

<sup>3</sup> For instance, SM2 model (Betti *et al.*, 2011), MAPP model (Baldini *et al.*, 2011), and the EUROMOD module for Italy (Sutherland and Figari, 2011) use IT-SILC data; while, TABEITA model (Ceriani *et al.*, 2013) and the microsimulation model developed by Pellegrino *et al.* (2011) considers as input data those provided by the Bank of Italy in the Survey on Households Income and Wealth (SHIW).

individual level questionnaire, besides information on education, health and occupation, detailed information on individual's income from various sources relevant for tax base assessment (employment, self-employment, old age and disability pensions, incapacity and disability benefits, rents from properties, investment income and other incomes) is covered. For income components subject to taxation<sup>4</sup>, the amount as net of taxes (and of social insurance contributions, where applicable) is collected, because net amounts are generally regarded as less exposed to measurement error and recall bias than gross ones. Reflecting the structure of the Italian fiscal system, where incomes earned in the solar year  $t$  are taxed in the following ( $t+1$ ), the reference period in income-related questions is the previous fiscal year, that is 2010. This represents a mismatch with respect to demographic information, which reflects the situation of households at the time when the fieldwork was carried out (i.e. March and April 2011), and which has therefore been brought backward to 2010.

Still, an accurate simulation of Italian personal income tax requires additional information with respect to IT-SILC topics coverage. Most notably, the personal income tax base includes not only employment and self-employment income, replacement income, profits from non-corporate enterprises and a marginal part of investment income, but also figurative income on immovable properties, valued as cadastral rent<sup>5</sup>, which is not covered in the survey. Besides, information on specific items of expenditures (e.g. healthcare, house refurbishments, etc.) that are relevant for specific tax reliefs, are not available in IT-SILC. Missing information has therefore been imputed, drawing from other population-representative surveys covering the subject domains of interest.

We use the 2010 Survey on Households Income and Wealth released by the Bank of Italy (Bank of Italy, 2012), for imputing information on the self-reported asset value<sup>6</sup> of the main residence, and other immovable properties, used to compute cadastral values. Drawing from the same survey, we also impute insurance premiums and house refurbishments expenditures, relevant for the computation of specific, and quantitatively important, tax reliefs. Imputation from SHIW has been performed using statistical matching techniques, where SHIW individuals have acted as 'donors' of the otherwise missing information for IT-SILC observed 'recipients'. Matching aims at selecting, for each IT-SILC recipient, the SHIW donor that is closest to observational identity, i.e. the most similar in terms of characteristics, observed in both surveys that are predictive of the variable to be imputed. The quality of the matching procedure relies crucially on a so-called

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<sup>4</sup> Non-taxable incomes and benefits are taken from the survey, rather than simulated, in order to obtain the disposable income measure.

<sup>5</sup> While cadastral income on the main residence is *de facto* exempted from personal income taxation through a tax deduction, it is anyway relevant for other components of the tax benefit system, such as the means test for family benefits. For other properties, according to whether they are rented or left unoccupied, the actual rent received or cadastral income are respectively used in tax base assessment.

<sup>6</sup> The SHIW question asks respondents to assess subjectively the value of each of their properties.

*common support* requirement of overlapping in the distribution of predictive characteristics in the donors' and recipients' samples, which has been empirically tested. The matching procedure we have adopted is based on a combination of stratification and Mahalanobis distance nearest neighbor algorithm (Rubin, 1980). Matching has been performed at the household level and with replacement, that is allowing the same SHIW household to act as donor for multiple IT-SILC households, if deemed as the most adequate, rather than being discarded after having served once as donor. The donors' and recipients' samples have been stratified by main residence homeownership, other properties homeownership and geographical area, so that exact matching on these variables is ensured; then, within each stratum, the donor household has been selected based on the Mahalanobis distance metric, measured on other predictive variables. These include equivalent household income, the percentage of household members with more than upper secondary educational qualification, a set of household composition dummies, and the main earner's employment status. The quality of matching has been gauged by investigating the balance (e.g. in terms of equality in means) in predictive variables between recipients and matched donors, and the procedure adjusted as long as achieved balance was deemed unsatisfactory. More detail on the implementation of the matching-based imputation, and the achieved balance, is reported in Appendix A.

As a result of the matching-based imputation from SHIW data, information on the asset value of owned properties is integrated into IT-SILC. However, for fiscal purposes, properties are valued in terms of cadastral rental values. Therefore, we build on existing Land Registry data, which provide information on the distribution of properties values and corresponding cadastral incomes (separately by gender, by age group, by household composition, by marital status, by geographical area and by main residence/secondary property) to derive a measure of cadastral income from the available information on properties asset values, integrated into IT-SILC. For assessing the cadastral value of the main residence, Land Registry information on the ratio between asset value and cadastral income is first of all expanded, using the RAS methodology<sup>7</sup>, to obtain marginal distributions across 300 subgroups, defined in terms of the above mentioned variables. After the IT-SILC sample has been correspondingly stratified, the cadastral value for IT-SILC households is computed as the ratio between the asset value of the main residence imputed from SHIW, divided by the corresponding asset-value-to- cadastral-income ratio<sup>8</sup>, drawn from the expanded Land

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<sup>7</sup> The RAS algorithm is an iterative proportional fitting procedure that estimates joint distribution of two or more variables given their marginal distributions. See Bacharach, 1965.

<sup>8</sup> More precisely, the ratio has been multiplied by a 1.05 correction factor, to reflect a legislated uprating adjustment.

Registry statistics. A similar procedure is followed for imputing the cadastral value of secondary properties, where appropriate<sup>9</sup>.

As an additional micro-data source, we use the 2013<sup>10</sup> MULTISCOPO Survey on Health Conditions and the Use of Health Services, released by the National Statistical Office (ISTAT, 2014), to impute information on healthcare expenditures, necessary to compute other major tax reliefs, namely those that involve the largest share of taxpayers. The MULTISCOPO survey has been used to estimate, at the individual level, the conditional probability of incurring in tax-relevant healthcare expenditures, such as specialists visits, drugs purchases, medical tests and treatments, as a function of predictive characteristics observed again both in MULTISCOPO and in IT-SILC. These include gender, six age groups, self-assessed health, reported chronic conditions, limitations in activities of daily living, geographical regions, marital status, occupation, education, presence of dependent children and household size<sup>11</sup>.

The estimated parameters have then been used to predict the probability of incurring in health expenditures for individuals observed in the IT-SILC sample, based on their characteristics. As illustrated in the later section 3.1, the estimated probability of healthcare spending is then flexibly used, together with fiscal data on tax reliefs, to identify beneficiaries of healthcare tax reliefs, and to impute related expenditure amounts.

### **3. THE CONSTRUCTION OF BETAMOD**

After the preliminary data adjustments and the imputations, the model has been built through 4 modules, integrated in an iterative procedure where outer loops (identifying recipients of tax expenditures, building calibration weights, computing individual- and income-specific tax evasion rates) feed into the inner loop of net-to-gross conversion, as depicted in Figure 1.

In more detail, based on family and personal characteristics relevant for eligibility, *Module 1* identifies round-specific beneficiaries and expenditure amounts for all of the non-simulated tax

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<sup>9</sup> When secondary properties are rented, the actual rent received, as collected in IT-SILC, rather than cadastral income, enters in the tax base definition.

<sup>10</sup> The MULTISCOPO Survey did not take place in 2010. Even though time distance between the interviews in IT-SILC 2010 and MULTISCOPO Survey 2013 seems quite large, this does not constitute an issue since we only used qualitative information that are actually comparable between the two datasets.

<sup>11</sup> We have not included income among the control variables since the MULTISCOPO Survey does not provide any information about it. However, research findings have suggested that, while at aggregate level there exists a positive and significant relationship between healthcare expenditure and GDP (Newhouse, 1977), at individual level, there is not a significant association between healthcare expenditure and income (especially when the health system provides universal coverage free of charge as the Italian healthcare system does). Indeed, full insurance coverage would remove the individual budget constraint and reduce or eliminate the influence of cost of care on patients' decisions of how much care to use. Typically, income elasticity of individual healthcare expenditure under full insurance coverage regime tends to be near zero (for details see Getzen, 2000).

reliefs<sup>12</sup>, calibrating them to obtain the totals and the income distribution for beneficiaries and expenditures resulting from administrative tax returns data. *Module 2* deals with the net-to-gross income conversion, through a standard iterative algorithm. Once gross and reported income measures have been obtained, *Module 3* estimates calibration weights in order to match both population totals and administrative taxpayers counts. By comparison of the grossed-up obtained income measures with disaggregated administrative tax returns data, *Module 4* produces an individual tax evasion rate which accounts for the individual's different income sources composition (employment income, pensions, self-employment income<sup>13</sup>, rental income from immovable property), the income level, and geographical residence (North-West, North-East, Center, South). After *Module 4*, round-specific convergence, measured in terms of equality between reported incomes as estimated by the model<sup>14</sup> and as resulting from official tax returns data<sup>15</sup> (both at the aggregate level, and by subgroups defined by main source of income and by geographical area), is assessed.

The overall iterative procedure, continues until convergence is achieved. Specifically, the iterations stop when the reported levels of income estimated by the model, reflecting estimated tax allowances, tax evasion rates and calibration weights, not differ significantly from official tax returns data, both at the aggregate level and by subgroups (defined by main source of income and geographical area). The overall procedure generates a battery of individual level variables, including true gross income, tax evasion rate, reported income, tax relevant expenditures, calibration weights, for later use in policy simulation modelling. The following sections provide in more detail the four modules and innovative aspects of the model construction.

### **3.1 Deductions and tax credits module**

In the Italian fiscal system there are different kinds of deductions and tax credits. The most sizeable, collectively worth over 5 per cent of GDP, are listed in Table 1, while a comprehensive list of tax reliefs, and their quantitative importance, is reported in Tables 6 and 7.

In terms of design, all deductions and tax credits are non-refundable, with the only exception of the tax credit granted to families with four children. Typically, an upper threshold applies to most

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<sup>12</sup> A comprehensive list of non-simulated tax reliefs, and of the individual and family characteristics used to identify the potential beneficiaries is reported in Tables 2 and 3.

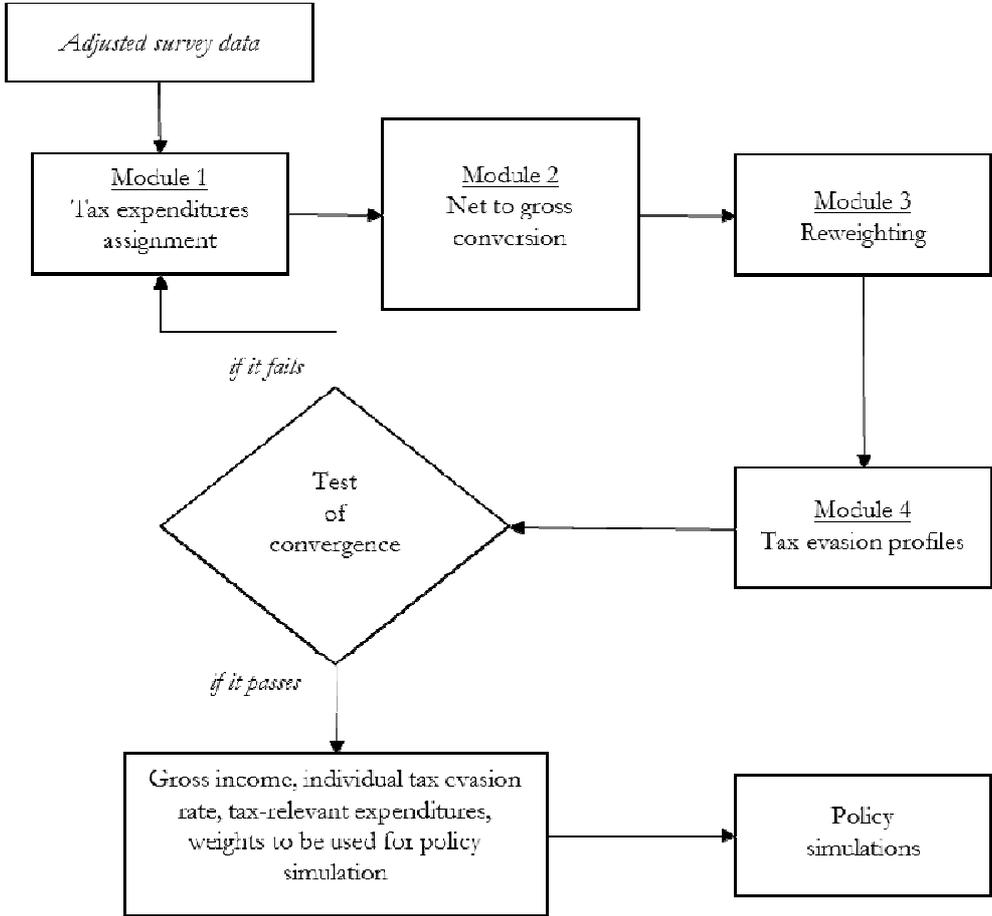
<sup>13</sup> We consider as self-employed members of the arts and or professions, sole proprietors, free lances, owners or members of a family business and persons receiving profits from non-corporate enterprises.

<sup>14</sup> By 'reported incomes as estimated by the model' we mean the portion of true gross income that we estimate the individual will declare, given his tax evasion rate. In what follows, this will be referred to as 'estimated reported income', as opposed to 'reported income', which refers to official tax returns data.

<sup>15</sup> The tax returns of the entire population of taxpayers are disposable on the website of the Italian Revenue Agency (Ministry of Economy and Finance) only in tabulated form (e.g. by type of income source, by income classes, by area of residence, etc.). Additional *ad-hoc* data were required for better modelling tax reliefs.

tax expenditures (mortgage interest payments, rent paid by tenants, education), while the healthcare tax credit is allowed on expenses in excess of a lower threshold. Also, a withdrawal rate often applies, so that the fiscal benefit is decreasing in individual's gross income<sup>16</sup>.

**Figure 1** The construction of BETAMOD



**Table 1** The largest PIT deductions and tax credits (fiscal year 2010)

Description	Value (millions of euros)	Percent of GDP
<i>Deductions</i>		
Social insurance contributions paid by self-employed individuals	17,603	1.13
Cadastral value of the main residence	8,283	0.53
Voluntary contributions to private pension plans	1,905	0.12
<i>Tax credits</i>		
Tax credit for specific income sources	41,887	2.70
Tax credit for dependent family members	11,375	0.73
Tax credit for healthcare expenditures	2,585	0.17

Source: Ministry of Economy and Finance, [http://www1.finanze.gov.it/analisi\\_stat/index.php?tree=2011](http://www1.finanze.gov.it/analisi_stat/index.php?tree=2011).

<sup>16</sup> The gross income qualified for tax reliefs is net of cadastral income on the main residence.

Among deductions, the most relevant in terms of number of recipients and lost revenue, are social insurance contributions paid by self-employed individuals<sup>17</sup>, the cadastral value of the main residence and voluntary contributions to private pension plans. Other deductions are granted for specific expenditures, including legal alimony payments to spouses, donations to religious institutions, personal care services and disability aids for the disabled, and social insurance contributions paid for domestic help.

Among tax credits, the largest single item is a universal tax credit granted for specific income sources: the tax credit is applicable for either employment income, or self-employment income, or pension income, with a withdrawal rate resulting in a decreasing credit as gross income increases. This tax credit contribute to the income tax progressivity design, even more so given the absence of a legislated no tax area or legal zero rate tax bracket.

Another set of tax credits aims at accounting for individual's ability to pay, given her/his household composition (i.e. presence of dependent household members) and her/his children characteristics, such as age and disability. These tax credits are decreasing in individual gross income and become zero above a certain income threshold. The children tax credit amount and income threshold depend also on the number of children, and increase for each child aged three years or below and for disabled children. An additional refundable tax relief is granted for taxpayers with at least four children.

Further tax credits are granted for specific expenditures, and amount to the 19 per cent of such expenditures: these include mainly healthcare, mortgage interest payments on both the main residence and other properties, life insurance premiums, secondary and tertiary education, childcare and charitable donations. Finally, a tax credits for up to a maximum of 55 per cent of the expenses incurred for energy conservation's interventions and house refurbishments, and a lump sum tax credit for rent paid by low-income tenants, are allowed.

As standard in other tax benefit models for the Italian system, and reflecting data availability constraints, BETAMOD fully simulates the deduction for main residence cadastral value, and the tax credits by income source and for dependent family members<sup>18</sup>. However, with respect to existing Italian models, which typically impute tax expenditures though calibration with aggregate fiscal data by income classes, BETAMOD improves by calibrating not only expenditure amounts, but also beneficiaries. In particular, we aim at achieving a more realistic identification of beneficiaries, for each specific type of tax expenditure item, based on household and personal

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<sup>17</sup> Employees' social contributions are not listed among deductions as they are excluded from taxable employment income.

<sup>18</sup> The simulation of tax credit for dependents required the construction of fiscal family that may not coincide with the definition of household adopted in IT-SILC. In fact, fiscal family members include the spouse, children and other relatives living with the referent person and having a personal gross income (before deductions) below € 2,840.

characteristics relevant for eligibility<sup>19</sup>. Table 2 and Table 3 report the individual and family characteristics we used to identify the potential beneficiaries of deductions and tax credits.

Simulated and non-simulated tax reliefs include all of the current categories provided by tax rules, namely, 8 deductions and 30 types of tax credits, these last grouped into 16 main categories. Thus, the model offers a complete picture of the wide array of tax reliefs that are part of the Italian income tax.

**Table 2** Deductions: identification of potential beneficiaries

<b>Deductions</b>	<b>Potential beneficiaries</b>	<b>Data source</b>
Social insurance contributions paid by self-employed individuals	having self-employed income	SILC
Cadastral value of the main residence	be the owner's of main residence	SILC
Voluntary contributions to private pension plans	those who reported to pay contributions to private pension plan	SILC
Legal alimony payments for spouse	those who reported to pay alimony	SILC
Personal care services and disability aids	identified by the estimated probability of healthcare spending	MULTISCOPO SILC
Social insurance contributions paid for domestic help	i) presence of children ii) having health care expenses	SILC
Donations to religious institutions	chosen among taxpayers with the higher probability of receiving other tax advantages	SILC
Others	chosen among taxpayers with the higher probability of receiving other tax advantages	SILC

<sup>19</sup> In practice, for certain tax reliefs, due to lack of information in the data, beneficiaries are mainly identified among the taxpayers with the higher probability of receiving other tax advantage; this is motivated by anecdotal evidence that the probability of claiming specific tax reliefs increases in the number of other tax reliefs claimed. In order to increase variance some beneficiaries have been randomly chosen.

**Table 3** Tax credits: identification of potential beneficiaries

	Potential beneficiaries	Data source
<b>19% tax credits</b>		
Healthcare expenses	identified by the estimated probability of healthcare spending	MULTISCOPO
Mortgage interest payments on main residence	i) be the homeowner's of main residence ii) have a mortgage loans for the purchase of the main residence	SILC
Life insurance premium	he/she have life insurance expenses	SHIW
Secondary and tertiary education	i) he/she is studying ii) have children attending high school or university	SILC
Funeral expenses	chosen among taxpayers with the higher probability of receiving other tax advantages	SILC
Mortgage interest payments on other properties	i) be the homeowner's of main residence and other properties	SILC
Annual enrollment to sports facilities	i) he/she is doing sport ii) have children between 6 and 18	SILC
Rent for resident students	have children attending university and not living within the same residence as the referent individual	SILC
Social/community/home care expenses	identified by the estimated probability of healthcare spending	MULTISCOPO
Charitable donations	chosen among taxpayers with the higher probability of receiving other tax advantages	
Real estate brokerage expenses	i) be the homeowner's of main residence ii) have a mortgage loans for the purchase of the main residence or others properties	SILC
Others	chosen among taxpayers with the higher probability of receiving other tax advantages	
<b>55% tax credits</b>		
For energy conservation's interventions	i) be the homeowner's of main residence ii) have expenses for energy conservation's interventions	SILC SHIW
<b>41%-36% tax credits</b>		
House refurbishments	i) be the homeowner's of main residence ii) have expenses for the refurbishment of buildings	SILC
<b>20% tax credits</b>		
<b>Lump sum tax credit</b>		
For tenants subject to controlled rent and for employees relocating closer to work	i) be for rent ii) have gross income less than € 30,987.41 iii) having age between 20 and 30 years old and gross income less than € 15,493.71	SILC
Security sector tax credit	i) be employee ii) have employment reported income less than € 35,000	SILC
Others	chosen among taxpayers with the higher probability of receiving other tax advantages	

Once potential beneficiaries have been identified, calibration of amounts and beneficiaries to fiscal data has been carried out for each tax relief type. Calibration accounts not only for income classes, as standard in other experiences, but also, building on the availability of additional *ad hoc* data obtained from the Ministry of Economy and Finance, for specific relief beneficiaries distribution across occupational status (employee, self-employed and pensioner) and number of dependent household members (none, one, two or more).

Overall, in the light of the importance of tax expenditures in current and future tax reform discussion (Burman, 2003 and 2008, MEF, 2011, Poterba, 2011, Tyson, 2014), BETAMOD can be used to estimate more accurately the revenue and distributional effects of all tax expenditures simultaneously and of specific tax reliefs or categories of expenditure.

### **3.2 Gross to net conversion module**

To derive gross incomes, we follow a widely used procedure based on an iterative algorithm (see, for instance, Immervoll and O'Donoghue, 2001), represented in Figure 2.

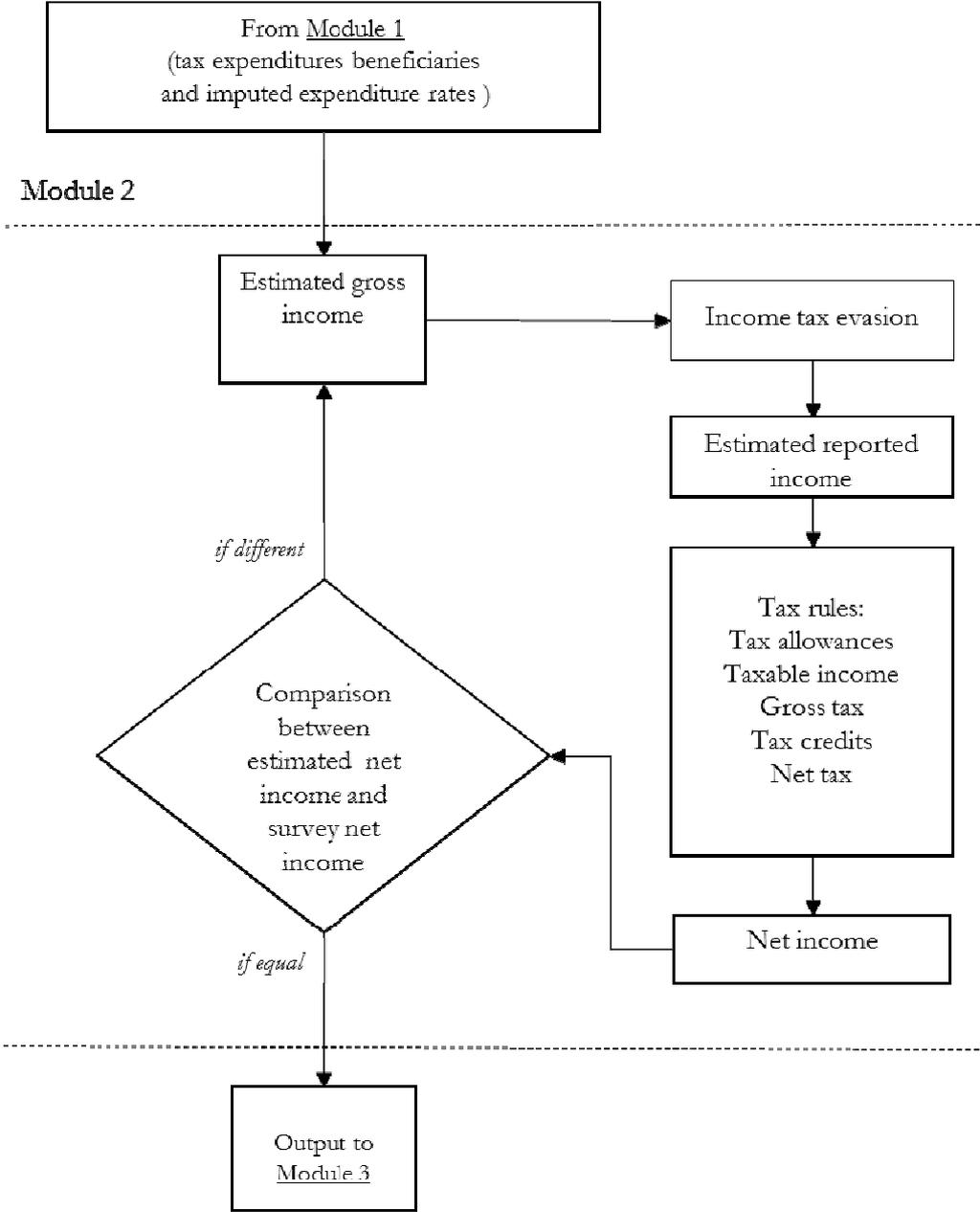
For each taxpayer the procedure estimates an initial true gross income based on an average tax rate applied to net income as collected in the survey, then applies an individual tax evasion rate, and then simulates the appropriate 2010 tax rules to produce a net income measure<sup>20</sup>, to be compared with the IT-SILC one.

If they differ, a new estimate of the true gross income is computed applying a correction factor, equal to the ratio between the original and the estimated net income, to the previous round true gross income and a new iteration is run. When equality between the two values is achieved (up to 1 euro of difference), the iteration ends and the data are sent to Module 3 for the reweighting procedure. The output for each individual, feeding into the following modules, includes true gross income, tax evasion rate, estimated reported income, deductions and tax credits, and gross and net income tax liability.

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<sup>20</sup> In computing individual tax liabilities, deductions are subtracted from reported income, to obtain taxable. The gross tax is calculated applying the tax schedule to taxable income. Then net tax is obtained subtracting tax credits from gross tax.

**Figure 2** Net-to- gross conversion (Module 2)



**3.3 Reweighting module**

Calibration weighting is a general technique for adjusting probability-sampling weights as of IT-SILC so that model estimates are consistent with external official data sources (among others, see Atkinson *et al.*, 1988; D’Amuri and Fiorio, 2006). As external data sources, we consider both population counts (from ISTAT official statistics) and official fiscal data (MEF).

While IT-SILC weights are built to match population totals (ISTAT), we adjust them to achieve consistency with fiscal data as well, so that the model estimates are reconciled with both the entire population and taxpayers counts. The variables used for performing the individual level

grossing-up are reported in Table 4. In addition to the standard socio-demographic variables, we also consider the number of taxpayers with dependent family members because of the important discrepancies between the sample distribution of household composition and official tax returns data. We obtain the joint distribution across those variables using the marginal distributions in a RAS-like iterative proportional fitting. The household weights are then computed by averaging individual household members weights<sup>21</sup>. As apparent in the last column of Table 4, the achieved difference between BETAMOD recalibrated weights and external official data totals are appealing with respect to model estimates representativeness.

**Table 4** The grossing-up results

Variable	IT-SILC weight	Official tax returns	BETAMOD weight	Difference
Total Population	60,683,909	-	60,683,909	0
Males	29,499,829	-	29,499,827	-2
Females	31,184,080	-	31,184,081	1
North West	16,131,196	-	16,131,196	0
North East	11,647,123	-	11,647,123	0
Center	11,943,354	-	11,943,354	0
South	20,962,237	-	20,962,237	0
Age 0 - 14	8,841,850	-	8,841,850	0
Age 15 - 24	6,041,469	-	6,041,468	-1
Age 25 - 44	17,172,717	-	17,172,717	0
Age 45 - 64	16,394,019	-	16,394,019	0
Age over 65	12,233,854	-	12,233,855	1
Total households	25,217,462	-	25,217,462	0
North West	7,186,593	-	7,186,593	0
North East	4,993,636	-	4,993,636	0
Center	5,007,637	-	5,007,637	0
South	8,029,596	-	8,029,596	0
Total Taxpayers	-	41,168,189	41,168,317	128
Males	-	21,622,165	21,622,249	84
Females	-	19,546,024	19,546,068	44
North West	-	11,653,491	11,653,533	42
North East	-	8,710,500	8,710,532	32
Center	-	8,317,613	8,317,638	25
South	-	12,486,585	12,486,613	28
<i>Reported income classes</i>				
1st quintile	-	8,359,593	8,357,026	-2,567
2nd quintile	-	7,753,926	7,754,008	82
3rd quintile	-	10,526,834	10,527,087	253
4th quintile	-	7,851,917	7,852,371	454
5th quintile	-	6,675,919	6,677,825	1,906
<i>Taxpayers by main income</i>				
Employment income	-	20,228,316	20,228,944	628
Pensions	-	14,165,864	14,166,862	998
Self-employment income	-	2,065,737	4,706,768	-1,504
Rental income from immovable property	-	4,708,272	2,065,744	7
Number of taxpayers with dependent family members	-	12,624,414	12624454	40

<sup>21</sup> An appropriate factor of correction is applied to ensure representativeness of households by geographical area.

### 3.4 The tax evasion module

According to the previous empirical literature concerning tax evasion at micro-level in Italy (Bernasconi and Marenzi, 1997; Florio and D'Amuri, 2006), we apply the “discrepancy method” to estimate tax evasion rates. The method, based on the assumption that individuals report a more truthful income to an anonymous interview than to fiscal authorities, computes tax evasion by comparing the tax returns and income survey responses of similar individuals.

In the above mentioned studies the comparison is made in terms of after-tax income. This choice has two main drawbacks. Firstly, it overestimate the tax evasion rates since it computes them as the ratio of evaded income on net income, instead of on true gross income. Secondly, when taxpayers are compared by quantiles of net incomes, a problem of re-ranking may arise. In fact, with respect to the distribution of after-tax income recorded in the survey, tax evasion shifts downwards individuals in the distribution of net income in the official data, so that, especially at low-income classes, the tax evasion rates are over-estimated. To overcome these drawbacks, BETAMOD estimates tax evasion rates as the percentage differences between the true gross incomes (as resulting from the net-to-gross conversion module) and the reported incomes declared to fiscal authorities. Clearly, since the true gross income is unknown and it is the results of the net-to gross procedure, tax evasion may be affected by approximations that depends on the estimation method.

Tax evasion rates are estimated in three steps (see Appendix B). In the first step, aggregate tax evasion rates, stratified by area and main income source type, are computed comparing simulated true gross incomes with administrative tax data on reported income. As administrative data are provided in aggregates, by main income source type and, separately, by geographical area, we first apply a RAS technique to obtain the joint distribution of reported income by both dimensions. As a result, a  $4 \times 4$  matrix of average evasion rates, by income type and geographical area, is obtained (see Table 9).

In the second step a distributional income profile of tax evasion is estimated for each area-by-income type stratum. We refine stratification expanding the 16 strata to account for the profile of tax evasion by income classes. In more detail, each area-by-income type stratum is expanded into 13 classes of true gross income, so that 16 income profiles of tax evasion are obtained. The design of each evasion-by-income profile results from an optimizing procedure, which aims at minimizing the distance between simulated and administrative reported income. The result is a  $16 \times 13$  dimension matrix of tax evasion rates by main income source type, geographical area and true gross income level.

Finally, a tax evasion rate is assigned to each individual for each type of income source to overcome the standard procedure of assigning the same tax evasion rate to all individuals in each matrix cell. BETAMOD selects randomly, within each cell, individuals to be identified as tax compliers, and those to be identified as tax evaders, then assigns individual tax evasion rates by using a beta distribution whose mean value is equal to the average tax evasion rate of the cell. Namely, individual tax evasion rates are calibrated so that the sum of individual evaded incomes is equal to the total income evaded in the class.

This represents an advancement, with respect to other models, where tax evasion rates are assumed to be constant within population subgroups (e.g. by income source type, by income classes). This feature allows assessing the relevance of re-ranking between tax-payers due to the presence of tax evasion.

#### **4. VALIDATION AND MAIN RESULTS**

The ability of BETAMOD to reproduce each measure (gross income, taxable income, deductions, tax credits and net tax liability) relevant for personal income tax and local income taxes is validated through a comparison with official figures provided by tax returns data for the relevant fiscal year, that is 2010.

To do this, we first compare the aggregate tax figures simulated by BETAMOD with the official fiscal statistics. Results are shown in Tables 5, 6 and 7. First, it should be noted that tax evasion reduces the true gross income of about 61 billions of euro, corresponding to an average tax evasion rate of 7.2 per cent (see Table 9). The estimated tax evasion rate might seem relatively low in a country, like Italy, where tax evasion is a widespread phenomenon (among others, Marino and Zizza, 2012; Fiorio and D'Amuri, 2006 and Murphy, 2012). However, the figure reflects the fact that employment income and pensions taken as a whole account for more than the 80% of total reported income (53% and 29%, respectively) and that the estimated average tax evasion rates for these two types of income are, respectively, 2.9 per cent and zero.

As apparent in Table 5, BETAMOD output and official fiscal data presents trivial (i.e. lower than 1%) differences in most figures achieving a very good performance in simulating revenues amounts and taxpayers' counts<sup>22</sup>.

The largest difference arises in the number of individuals with positive gross tax liability. This seems mostly driven by the model imputation of tax deductions, resulting in a larger number of individuals with positive taxable income in BETAMOD. This is because tax deductions have been

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<sup>22</sup> The regional income tax is simulated by BETAMOD while the municipal income tax is imputed.

imputed as a percentage of reported income, thus constraining their amount to be lower than reported income, and therefore taxable income to be positive, by construction.

Focussing on deductions, Table 6 reports the number and the amount of beneficiaries for each type.

**Table 5** Aggregate validation: main components of personal income tax and local taxes

	Number of taxpayers <sup>1</sup>			Value <sup>2</sup>		
	BETA-MOD	Official tax returns	Diff %	BETA-MOD	Official tax returns	Diff %
Totals						
True gross income	41,168	-	-	853,891	-	-
Evaded income	14,778	-	-	60,789	-	-
Reported gross income	41,168	41,168	0.0	793,102	792,520	0.1
Deductions	13,794	13,374	3.1	21,736	21,746	0.0
Taxable income	41,097	39,894	3.0	763,086	762,185	0.1
Gross tax	41,097	39,078	5.2	205,213	205,613	-0.2
Tax credits	39,977	39,088	2.3	64,604	62,482	3.4
Net tax liability	31,178	30,897	0.9	147,904	149,443	-1.0
Regional income tax	31,035	30,653	1.2	8,655	8,633	0.3
Municipal income tax	25,251	25,265	-0.1	3,023	3,021	0.1

Notes: <sup>1</sup> thousands of persons - <sup>2</sup> millions of euros.

**Table 6** Aggregate validation: deductions

Deductions	Number of taxpayers <sup>1</sup>			Value <sup>2</sup>		
	BETA-MOD	Official tax returns	Diff %	BETA-MOD	Official tax returns	Diff %
Social insurance contributions paid by self-employed individuals	11,922	11,991	-0.6	17,601	17,603	0.0
Cadastral value of the main residence	16,873	17,166	-1.7	8,279	8,283	0.0
Voluntary contributions to private pension plans	803	822	-2.3	1,897	1,905	-0.4
Legal alimony payments for spouse	109	120	-9.5	742	745	-0.4
Personal care services and disability aids	147	143	2.8	537	531	1.2
Social insurance contributions paid for domestic help	522	537	-2.8	415	419	-0.9
Donations to religious institutions	95	104	-8.7	27	27	-1.8
Others	1,800	1,816	-0.9	517	516	0.1

Notes: <sup>1</sup> thousands of persons- <sup>2</sup> millions of euros.

Again, no significant differences are found between BETAMOD results and tax returns data, in particular, BETAMOD replicates well the largest deduction (the social insurance contributions).

Some discrepancies can be observed only in simulating the number of deduction beneficiaries for donations to religious institutions (-8.7%) and for alimony payments to the spouse (-9.5%). In both cases the number of tax relief claimants is anyway negligible.

Table 7 considers tax credits, covering both the model-simulated and the imputed ones. In general, BETAMOD estimates provide a good approximation of the tax returns figures.

**Table 7** Aggregate validation: tax credits

Tax credit	Number of beneficiaries <sup>1</sup>			Value <sup>2</sup>		
	BETA-MOD	Official tax returns	Diff %	BETA-MOD	Official tax returns	Diff %
Income source tax credit	37,852	36,426	3.9	44,475	41,887	6.2
Dependent family members tax credit	12,624	12,624	0.0	10,914	11,375	-4.0
<b>19% tax credits</b>						
Healthcare expenses	14,855	15,002	-1.0	2,588	2,585	0.1
Mortgage interest payments on main residence	3,817	3,841	-0.6	1,146	1,147	0.0
Life insurance premium	6,437	6,520	-1.3	750	751	-0.1
Secondary and tertiary education	2,102	2,095	0.3	318	318	0.0
Funeral expenses	413	428	-3.6	119	119	-0.4
Mortgage interest payments on other properties	281	296	-5.1	80	77	3.2
Annual enrollment to sports facilities	1,506	1,522	-1.1	60	60	0.1
Rent for resident students	159	169	-6.2	51	50	1.0
Social/community/home care expenses	113	108	4.0	38	38	0.6
Charitable donations	899	915	-1.8	36	36	0.3
Real estate brokerage expenses	95	100	-4.1	16	15	1.5
Others	1,080	1,101	-1.9	83	83	-0.1
<b>55% tax credits</b>						
For energy conservation's interventions	1,038	1,052	-1.4	1,351	1,349	0.1
<b>41%-36% tax credits</b>						
House refurbishments	5,175	5,267	-1.8	2,242	2,243	0.0
<b>20% tax credit</b>						
Others tax credits	539	540	-0.1	65	65	-0.1
<b>Others tax credits</b>						
For tenants subject to controlled rent and for employees relocating closer to work	708	713	-0.7	138	136	1.5
Security sector tax credit	375	349	7.5	50	50	0.0
Others	158	137	15.3	84	83	1.6

Notes: <sup>1</sup> thousands of persons- <sup>2</sup> millions of euros.

The number of beneficiaries and the amount of the income-source tax credit are overestimated of about 3.9% and 6.2% respectively. This is mainly due to the fact that estimated reported incomes are more dense in the bottom of the distribution in BETAMOD than in tax data. Since the tax credit is decreasing in income, the BETAMOD tax credit results greater than in tax returns data. As to the dependent family members tax credit, the striking similarity in the number of beneficiaries is motivated by this variable having been taken into account in the weighting design, while the simulated amount of tax credit is -4.0% lower than the official figure, presumably reflecting the sample distribution of household composition, relevant for identification of dependants. The other most sizeable tax credits, namely healthcare expenditures<sup>23</sup>, house refurbishment, energy interventions and mortgage interest tax credits are remarkably close to the administrative figures. As expected, the main discrepancies arise in the numbers of beneficiaries of the less sizeable tax credits<sup>24</sup>.

Besides assessing the model validity at the aggregate level, no less attention should be devoted to the validation of the distributional patterns of different components of the model output, as it mainly represents a tool for carrying out distributional analyses. First, we compare the distribution of taxpayers (Figure 3) and of simulated reported income (Figure 4) with official statistics. Overall, the BETAMOD distributions are strikingly similar to the fiscal data ones, especially in the classes of reported income where most of taxpayers fall (12-26 thousands of euros). Such pattern of similarity is confirmed when considering the distribution of average gross and net tax liabilities across income classes (Table 8).

The following Figures 5 and 6 represent the progressive design of the income source and the family dependents tax credits, as arising from BETAMOD and from tax returns data. Again, the similarity between the two is striking, and is also confirmed for other tax allowances (the related figures are reported in Appendix C). Interestingly, both tax credits are partly lost by taxpayers in the bottom income class, due to their low level of taxable income/gross tax liability, and to the non-refundable nature of these tax credits.

As evidenced in previous Tables 6 and 7, tax deductions and tax credits subsidize personal spending on a wide range of goods and services, including housing, healthcare and education. Some preliminary information on the model assessment of the redistributive impact of those tax reliefs that substitute direct expenditures<sup>25</sup> is provided in Table 9. Were tax expenditures abolished, state and local tax revenue would be raised by 15,100 millions of euros (+10% with

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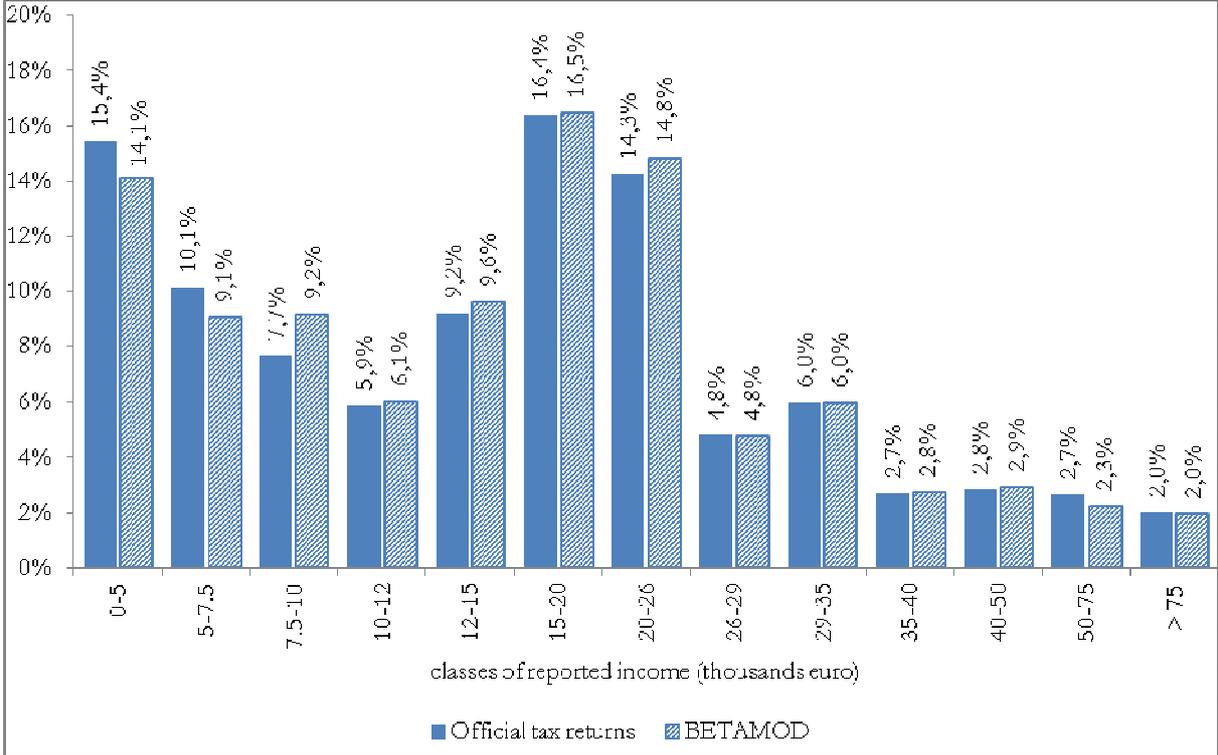
<sup>23</sup> Among tax credits granted for specific expenditures, healthcare expenditures represents about the 49%.

<sup>24</sup> Simulating the correct number of beneficiaries in the quantitatively less important tax credits is, in fact, one of the most common challenges in microsimulation modelling due to the lack of information relevant for identification of potential claimants in the survey data, as well as to the small number of individuals involved.

<sup>25</sup> For the exercise we consider all tax reliefs excluding income source and dependent family members tax credits.

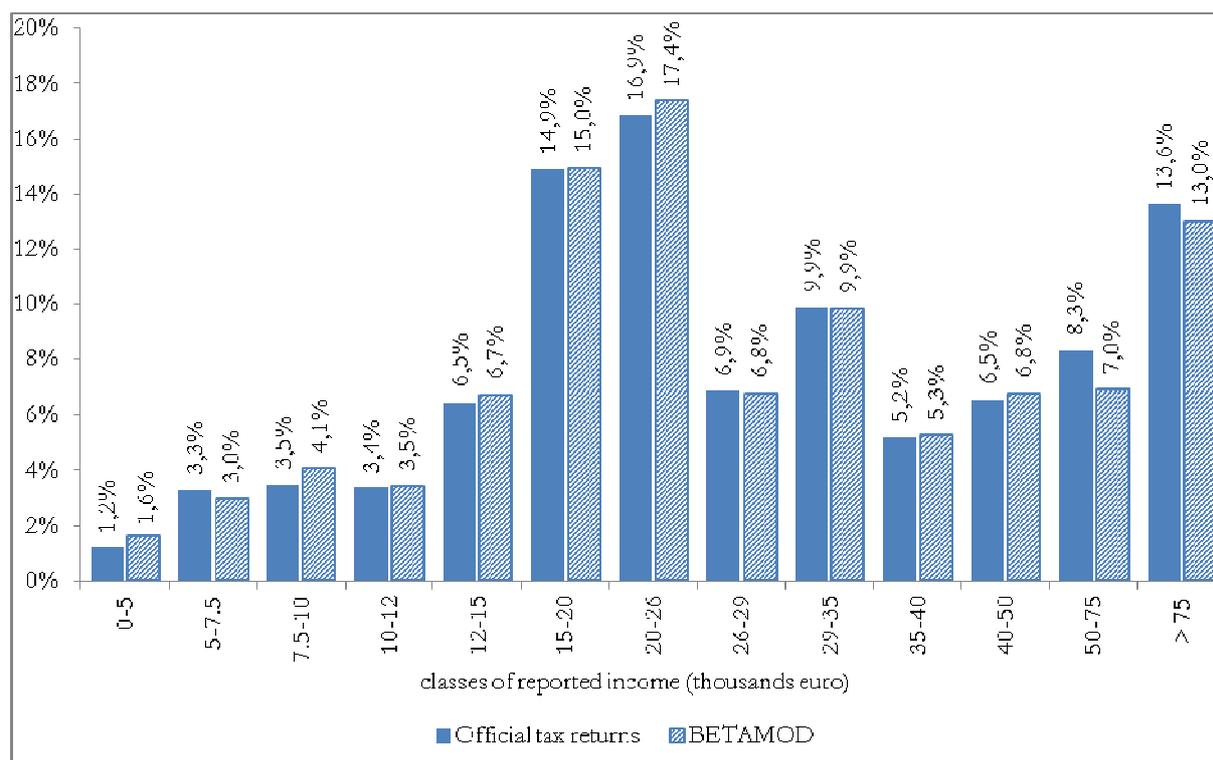
respect to the baseline simulation) and inequality indexes reduced of about 0.35%. Although the “revenue method” does not account for taxpayers’ behavior (see, Burman *et al.*, 2008), deductions and tax credits appear to generate a more unequal distribution of households’ equivalent disposable income<sup>26</sup>.

**Figure 3** Distribution of taxpayers by classes of reported income



<sup>26</sup> We compute household’s disposable income by adding all true gross income earned by the family members and subtracting the personal tax liabilities. The household equivalent income is obtained by applying the OECD-modified equivalence scales.

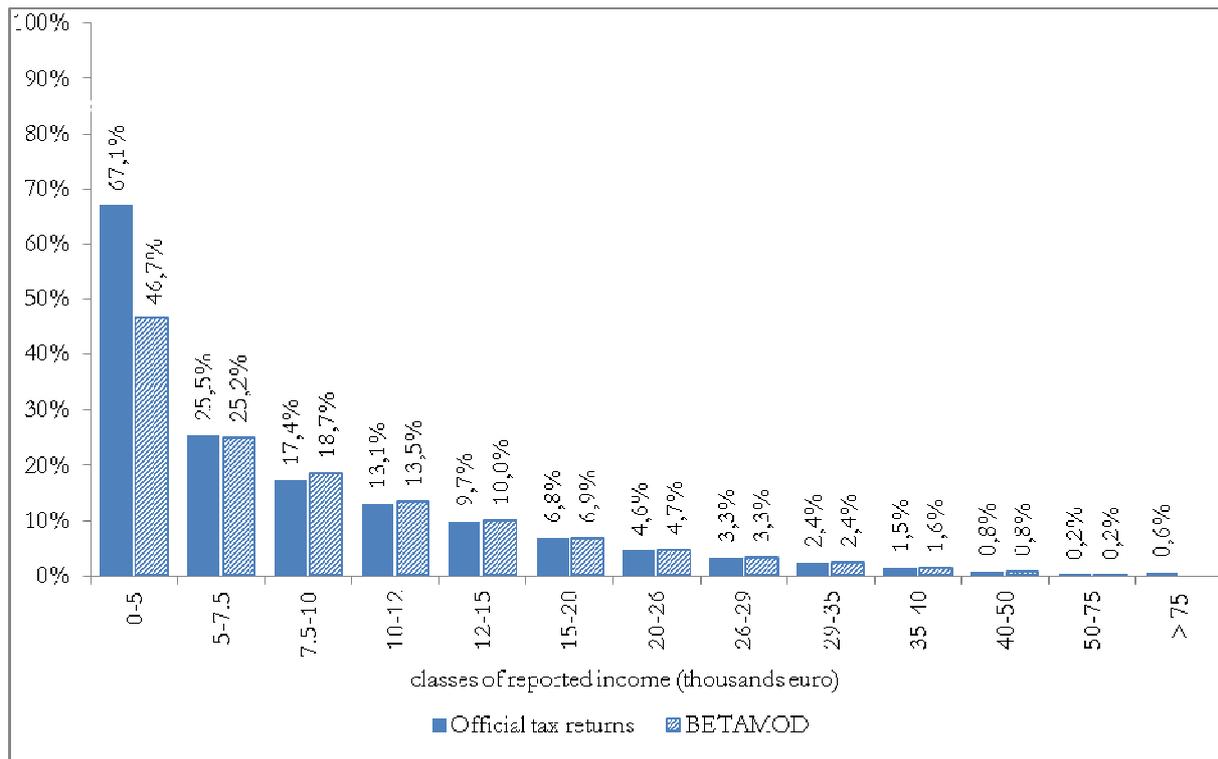
**Figure 4** Distribution of reported income by classes of reported income



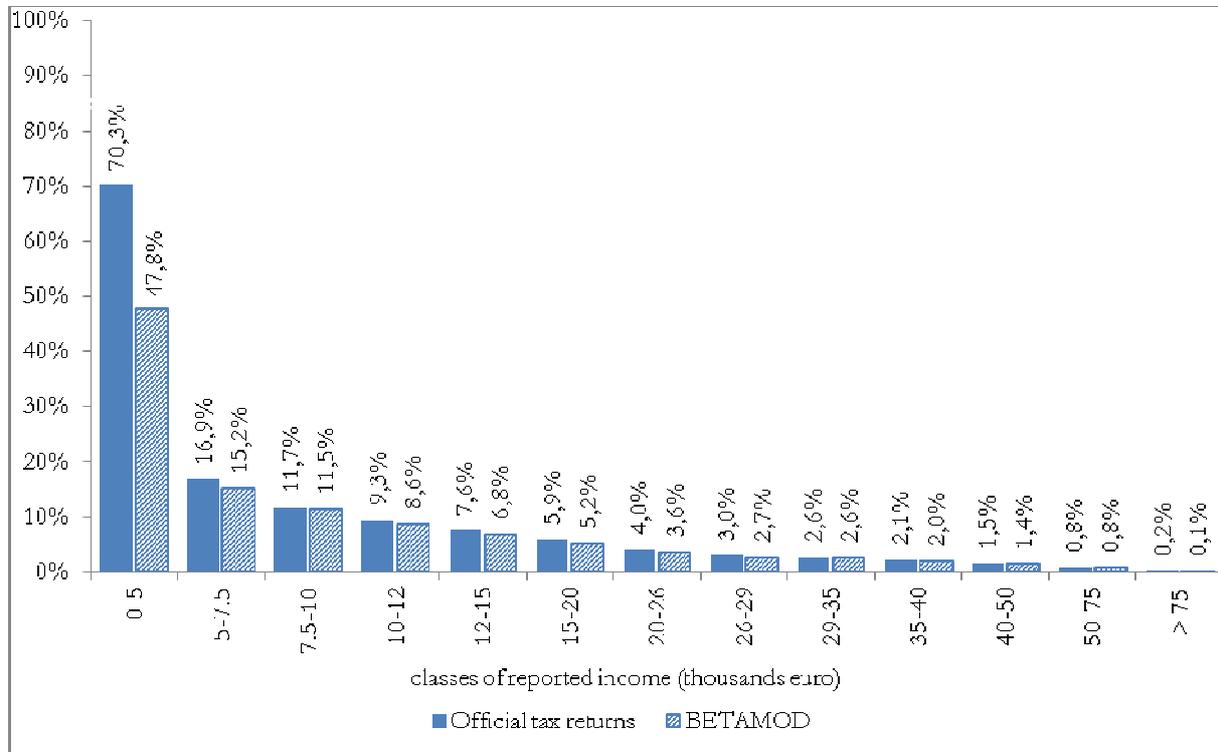
**Table 8** Gross and net tax distribution by income classes (mean values in euros)

Classes of reported income (euros)	Gross tax		Net tax	
	BETAMOD	Official tax returns	BETAMOD	Official tax returns
0 – 5,000	442	453	281	229
5,000 - 7,500	1,317	1,394	613	460
7,500 - 10,000	1,851	1,938	415	492
10,000 - 12,000	2,437	2,417	826	867
12,000 - 15,000	2,998	2,993	1,384	1,426
15,000 - 20,000	4,005	3,988	2,373	2,336
20,000 - 26,000	5,363	5,359	3,745	3,673
26,000 - 29,000	6,612	6,584	5,026	4,952
29,000 - 35,000	7,979	7,966	6,403	6,401
35,000 - 40,000	10,077	9,962	8,763	8,513
40,000 - 50,000	12,634	12,439	11,452	11,169
50,000 - 75,000	18,111	18,244	17,134	17,228
above 75,000	45,707	46,799	44,166	45,551
Average	4,993	5,262	4,744	4,837

**Figure 5** Income source tax credit as a proportion of reported income (%)



**Figure 6** Tax credit for dependent family members as a proportion of reported income (%)



**Table 9** Effect on inequality of tax expenditures

<i>Tax law 2010</i>		
Gini index	32.55%	
Atkinson index	18.35%	
<i>Removal of deductions</i>		<i>Variation</i>
Gini index	32.32%	-0.23%
Atkinson index	18.14%	-0.20%
<i>Removal of tax credits</i>		<i>Variation</i>
Gini index	32.40%	-0.15%
Atkinson index	18.20%	-0.14%
<i>Removal of both deductions and tax credits</i>		<i>Variation</i>
Gini index	32.17%	-0.38%
Atkinson index	17.99%	-0.35%

### 5. Tax evasion and its distributional profile

To showcase BETAMOD potential for analysis, in this section we provide some distributional evidence on tax evasion. According to our estimates, on aggregate €61 billions of gross income escape tax authorities, corresponding to a tax revenue loss amounting to about €16 billions<sup>27</sup>. Unsurprisingly, tax evasion arises mostly from self-employed income and, to a lesser extent, rental income from property: overall, 85% of evaded income is attributable to these two sources (65% and 20% respectively). The remaining 15% of evaded income is attributable to employment income, as pension income, representing a public transfer, can hardly be hidden from tax authorities.

Average tax evasion rates, by income source and geographical area, are reported in Table 10. The figures reveal that tax evasion on employment income, while not negligible, is low (2.9%), and that the largest tax evasion rates are registered on rental income from immovable property (33.6%) and self-employment income (24%). Relevant differences arise also between geographical areas: in particular, our results identify individuals living in the South of Italy as those displaying systematically higher tax evasion rate, followed by those in the North East. The BETAMOD estimated average values are slightly lower, yet not inconsistent, with estimates derived by above mentioned studies on tax evasion in Italy.

<sup>27</sup> The tax revenue loss refers to the personal income tax (15 billions), regional and municipal additional income taxes (800 and 160 millions respectively).

**Table 10** Average tax evasion rates by income source and geographical area (%)

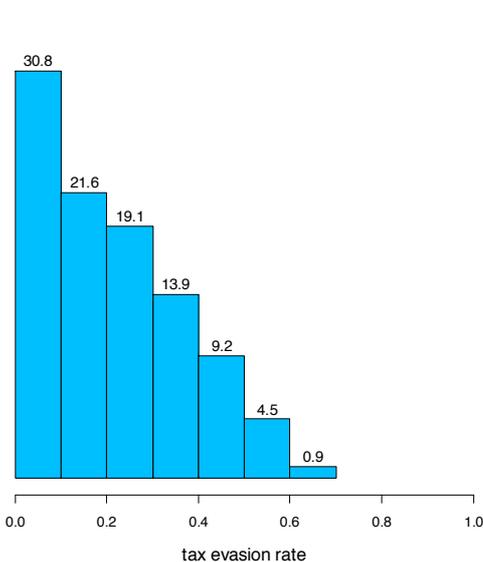
Average tax evasion rate	NW	NE	C	S	Italy
Employment income	2.7	3.1	2.8	3.3	2.9
Pensions	0.0	0.0	0.0	0.0	0.0
Self-employment income	22.2	25.1	22.3	27.2	24.0
Rental income from immovable property	30.6	35.5	31.3	38.2	33.6
Total income	6.9	7.5	6.8	7.7	7.2

As arises from Figure 7 (*a,b,c*), the distribution of tax evasion rates varies across different income sources. Among individuals who hide employment income from tax authorities, low tax evasion rates are most often estimated. On the contrary, more than half of self-employed income tax evaders display a tax evasion rate that is higher than 60%. A similar distribution arises for rental income evasion; about 50% of rental income tax evaders display tax evasion rates between 60 and 80%. Figure 7*d* plots the full distribution of estimated individual tax evasion rates, by true gross income, i.e. the ‘true’ amount individuals would report to tax authorities under full compliance. The Figure reveals that individuals’ tax evasion rates cluster around an upper and a lower level, reflecting the underlying individual income sources composition, i.e. the prevalence of employment (relatively low level of tax evasion) versus self-employed and rental incomes (high level of tax evasion). The evidently negative gross income gradient of tax evasion rates clearly reflects the tax evasion estimation procedure, which accounts for evasion-by-income profiles<sup>28</sup>. The following Figure 8, where tax evasion rates by income class are shown, provides further evidence on the negative gross income gradient of tax evasion rates, and allows to better gauge the income profile of tax evasion behaviour by income source as well. In relative terms, both for each income source, and for their aggregate, consistently with previous studies, BETAMOD reflects tax evasion rates generally decreasing in income<sup>29</sup> (although to a much lesser extent in the lowest income classes, with respect to other classes).

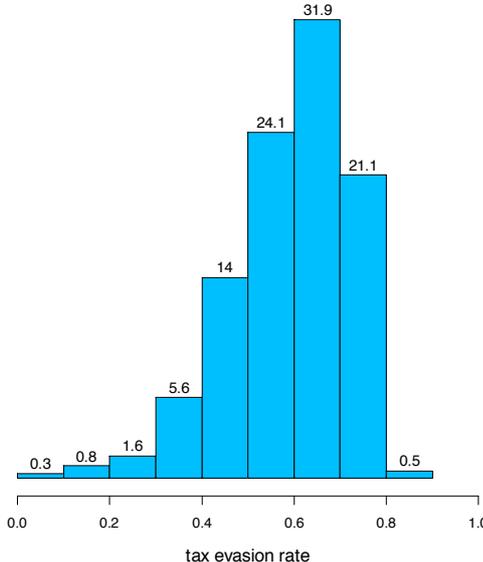
<sup>28</sup> As previously explained in section 3.4, the decreasing aggregate profile results by the comparison between BETAMOD simulated gross income and reported income to tax authorities.

<sup>29</sup> Results must be considered taking into account that they are based on the income distribution which directly emerges from IT-SILC survey. However, the survey doesn’t guarantee representation of true income distribution. Previous studies, although based on Bank of Italy’s survey (e.g. Cannari and D’Alessio, 1992) have in particular identified two major biases, which are indeed common to surveys conducted in other countries. The first is the selectivity bias due to the fact that not all families are equally available to participate to the survey; the second is known as under-reporting, and arises when the respondent reports a disposable income below the true income. Both selectivity bias and under-reporting can be explained with the fear that some people have that their files could be accessed by the tax authorities. Evidence indicates that the fear is more pronounced in individuals belonging to the upper tail of the distribution. A third, though less relevant, bias is originated by some over-reporting of people belonging in the lower tail. Clearly all three biases contribute to making the sample distribution less unequal than the real distribution.

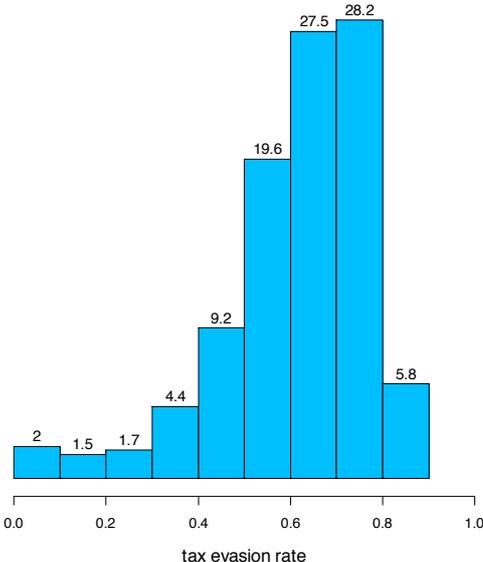
**Figure 7** Distribution of tax evasion rates by type of income (tax evaders only, in percentage)



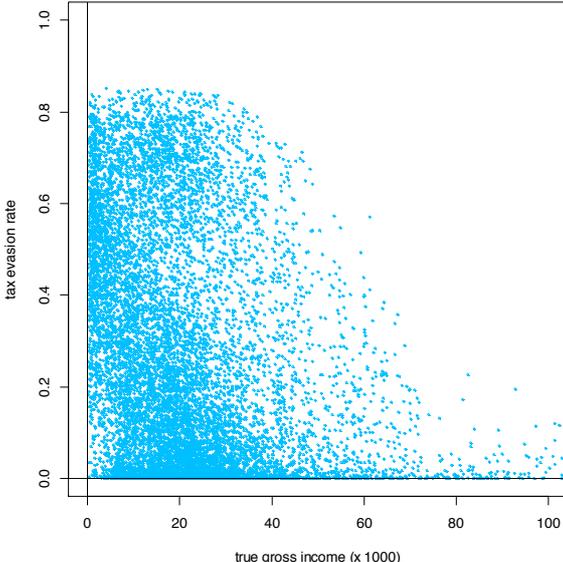
*a) employment income*



*b) self-employment income*



*c) rental income from immovable property*



*d) individual tax evasion rates*

**Figure 8** Average tax evasion rates by type of income and by true gross income classes

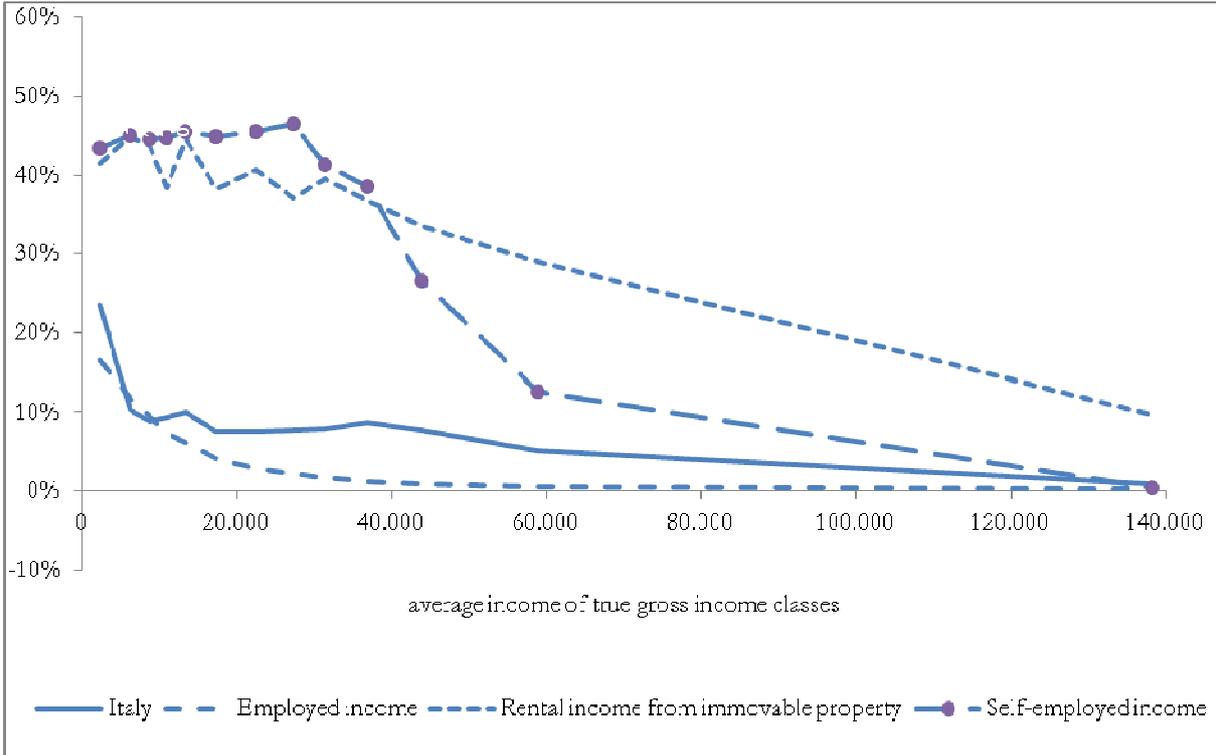
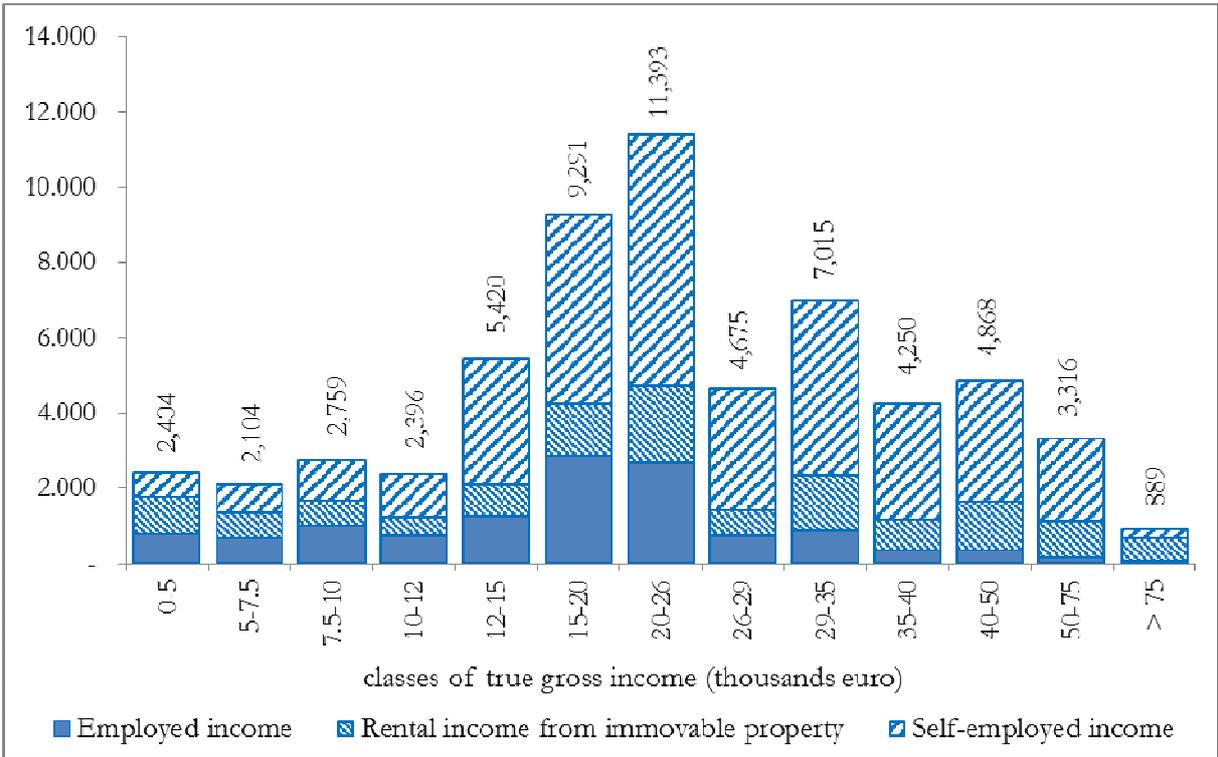


Figure 9 shows the total amount of unreported income. It can be noticed that, despite the decreasing profile of tax evasion rates, most of evaded income is due to taxpayers with gross income in the range 12,000-50,000 euro, and mainly to self-employed income.

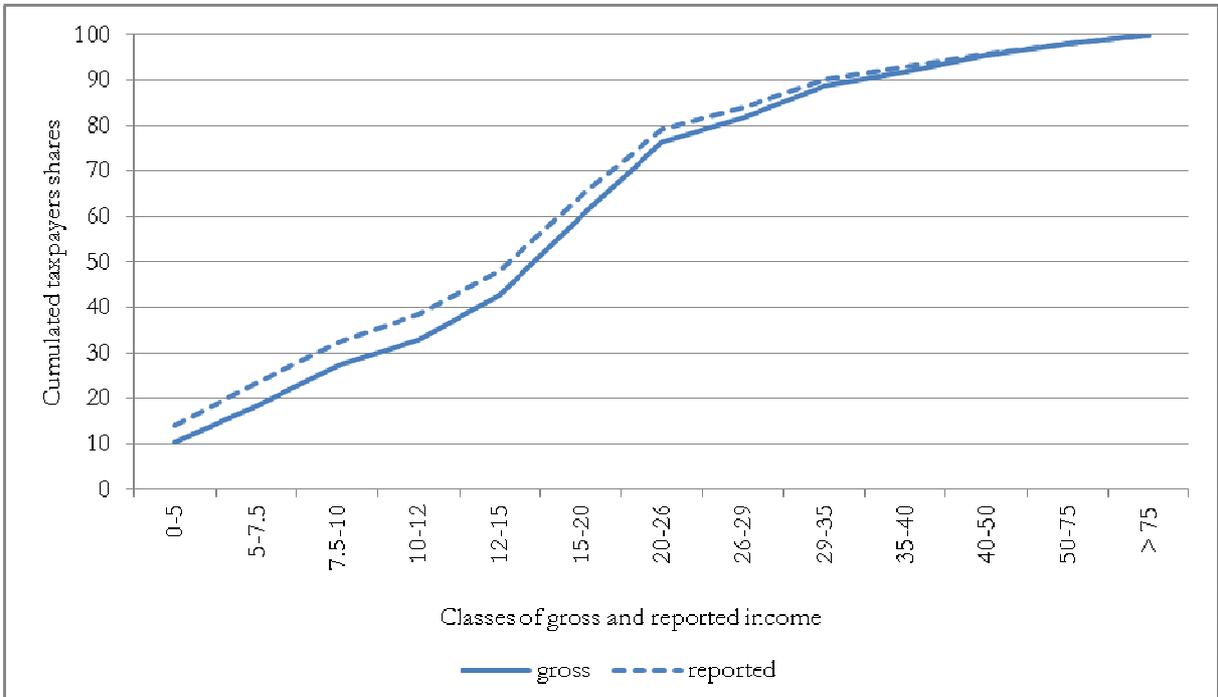
Tax evasion, by reducing reported income, causes a relevant downward shift in the distribution of taxpayers by reported income, with respect to that by (true) gross income. To begin with, tax evasion may modify the relative position (in terms of reported income) between fully-compliant taxpayers and same-true-gross-income evaders, generating an horizontal inequity effect in income taxation. Indeed, while horizontal inequity is one of the major consequence of tax evasion, very little studies measuring it exist.

BETAMOD evidence is provided in Figure 10, where the two cumulative distributions of taxpayers, by (true) gross and reported income respectively, are shown. The distribution of individuals by reported income is thicker in the left tail, when compared with the distribution of gross income, suggesting a downward movement, along the income distribution, of taxpayers who “benefit” from tax evasion.

**Figure 9** Unreported income by classes of true gross income (millions of euros)



**Figure 10** Cumulative distributions of taxpayers by (true) gross and reported income classes



BETAMOD transition matrix, reporting the share of true gross income taxpayers falling in each income class, found in different reported income classes as a result of tax evasion, is reported in Table 11. As a result of non-compliance, the taxpayers in the bottom income class, for instance, moves from about 10% when considering true gross income to about 14% when considering reported income relevant for taxation. Evaders who enter the bottom income class come from the 2<sup>nd</sup> to the 8<sup>th</sup> income class (up to 29 thousands of euros), rather than from higher income classes, reflecting the decreasing income profile of tax evasion rates. Moving to the upper classes, we observe a similar pattern of shifts across income classes, although the number of shifts is progressively reduced, again because of the negative income gradient in tax evasion. While Table 10 only reports between class shifts, building on the availability of individual tax evasion rates, BETAMOD allows to detect further shifts happening within each income class.

Once taxation applies to reported income, shifts along the income distribution, give rise not only to horizontal inequities, but also to a re-ranking effect, with a reversal of taxpayers' relative positions before (i.e. reflecting the true gross income position) and after personal income taxation ( i.e. based on the reported income position ), which the model also allows studying. Although preliminary, the novel empirical evidence showcased here bears major implications for the accurate measurement of the actual redistributive effect of personal income taxation and its decomposition in the horizontal, vertical and re-ranking effect, each of which is possibly altered by tax evasion.

**Table 11** Transition matrix of taxpayers from (true) gross income to reported income (%)

		Classes of true gross income												Total	
		0-5	5-7.5	7.5-10	10-12	12-15	15-20	20-26	26-29	29-35	35-40	45-50	50-75		> 75
Classes of reported income	0-5	10.47	1.51	0.79	0.33	0.57	0.33	0.11	0.01						14.11
	5-7.5		6.37	0.91	0.43	0.42	0.52	0.32	0.07	0.04					9.08
	7.5-10			7.13	0.60	0.49	0.34	0.39	0.11	0.08	0.02				9.15
	10-12				4.38	0.71	0.50	0.25	0.06	0.11	0.04	0.01			6.06
	12-15					7.66	1.25	0.31	0.08	0.17	0.09	0.04			9.61
	15-20						14.26	1.64	0.24	0.19	0.09	0.05			16.5
	20-26							13.43	0.72	0.43	0.12	0.11	0.01		14.82
	26-29								4.06	0.51	0.12	0.08	0.01		4.78
	29-35									5.34	0.37	0.23	0.06		6.01
	35-40										2.38	0.31	0.05		2.75
	40-50											2.64	0.30		2.94
	50-75												2.25	0.02	2.26
	> 75													1.95	1.95
	Total		10.47	7.88	8.83	5.74	9.85	17.21	16.45	5.36	6.86	3.23	3.48	2.67	1.96

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## Appendix A - Statistical matching between the IT-SILC and SHIW datasets

We describe here how the statistical matching between the IT-SILC dataset with the Bank of Italy's Survey on Households Income and Wealth (SHIW) at the household level was performed. First, two constraints need be satisfied to make matching feasible: (i) the two surveys must be random samples from the same population; (ii) there must be a common set of conditioning variables. In our case, the first condition is met by design, since both the IT-SILC 2011 and the SHIW 2012 data are representative of the Italian population. As far as the second constraint is concerned, the variables ( $X$ ) common to each dataset and chosen for the process of imputation of self-reported asset value of the main residence, insurance premiums and house refurbishments expenditures are: equivalent household income, the percentage of household members with more than upper secondary educational qualification, a set of household composition dummies, and the main earner's employment status. The final sample is made up of 7.951 households from the SHIW survey and 19.399 households from the IT-SILC Survey.

The dataset, integrated by IT-SILC -Bank of Italy was created using the Mahalanobis Distance Matching Method (MDMM), a statistical method which allows individuals with similar characteristics but from different datasets to be paired (Rosenbaum and Rubin, 1983). In order to obtain a more precise matching, the sample was stratified in cells according to the main residence homeownership, other properties homeownership and geographical area so that exact matching on these variables is ensured; then, within each stratum, the donor household has been selected based on the Mahalanobis distance metric, measured on the other  $X$  variables.

The Mahalanobis metric is a measure of dissimilarity between observation which measures the distance between units  $i$  from the recipient dataset IT-SILC and  $j$  from the donor dataset SHIW weighting each coordinate of  $X$  in inverse proportion to the variance of that coordinate:

$$d(i, j) = (x_i - x_j)\Sigma^{-1}(x_i - x_j)'$$

Where  $\Sigma$  is the variance–covariance matrix of  $X$ .

Matching has been performed at the household level and with replacement, that is allowing the same SHIW household to act as donor for multiple IT-SILC households, if deemed as the most adequate, rather than being discarded after having served once as donor.

Once the matching procedure was complete, we check the quality of the matching. The quality of matching was evaluated in terms of maintaining the asset value of the main residence, insurance premiums and house refurbishments expenditures distributions, both in terms of preserving the pre-existing variables distribution as well as in terms of pre-existing relations between variables of interest. The next step was i) the comparison between the asset value of the main residence, insurance premiums and house refurbishments expenditures distributions in the integrated

dataset and the pre-existing SHIW one, ii) the calculation of the correlation between asset value of the main residence, insurance premiums and house refurbishments expenditures distributions and the  $X$  vector to verify the maintenance of the sign recorded in the "donor set". The differences between the common-fusion correlations in the SHIW data set versus the fused IT-SILC data set were well preserved for most variables. For the sake of brevity, tables showing distributions and correlations are not included but they are available on request.

Finally, the quality of the matching has been evaluated in terms of "balancing test": we compared the mean covariate values in the recipients and matched donors i.e. each of the observable covariates within the recipients has the same average value within the matched donors. Before matching we expect differences, after matching the variables should be balanced in both groups and significant differences should not persist.

The covariate balancing test, included in Table A1, shows that the matching is effective in removing differences in observable characteristics between the recipients and matched donors. In particular, the median absolute bias is reduced by approximately 82%-98%. The Pseudo R-squared after matching is always close to zero, correctly suggesting that the covariates have no explanatory power in the matched samples. The chi-square test conducted before and after matching, proves that the propensity score removed bias due to differences in covariates between the recipients and matched donors.

**Table A.1** Balancing Test

Property		Region				Sample	Pseudo R2	LR test	p-values	Median Bias	% reduction in median bias
1 <sup>st</sup>	2 <sup>nd</sup>	N-O	N-E	C	S						
✓		✓	✓			Before matching After matching	0.013 0.000	99.72 0.38	0.000 0.996	6.4 0.2	0.969
✓				✓		Before matching After matching	0.012 0.000	42.77 1.23	0.000 0.942	5.0 0.1	0.980
✓					✓	Before matching After matching	0.019 0.000	102.27 1.30	0.000 0.935	5.8 0.4	0.931
✓	✓	✓				Before matching After matching	0.007 0.000	11.84 0.07	0.037 1.000	6.7 0.3	0.955
✓	✓		✓			Before matching After matching	0.001 0.001	2.50 2.27	0.776 0.810	4.2 0.3	0.929
✓	✓			✓		Before matching After matching	0.007 0.000	14.36 0.20	0.013 0.999	6.0 0.4	0.933
✓	✓				✓	Before matching After matching	0.004 0.000	9.31 0.63	0.097 0.987	7.0 0.2	0.971
	✓	✓	✓	✓	✓	Before matching After matching	0.004 0.001	4.14 1.46	0.529 0.917	4.6 0.8	0.824
		✓	✓			Before matching After matching	0.042 0.000	136.58 1.95	0.000 0.857	6.1 0.1	0.984
				✓	✓	Before matching After matching	0.029 0.000	122.41 0.51	0.000 0.992	10.0 0.2	0.980

## Appendix B – Estimation of tax evasion rates

### B.1 Tax evasion rates by income source type and geographical area

From official tax returns data (from MEF) we know the total amount of reported income and the number of taxpayers by *main* income source type ( $i = 1, \dots, 4$ ) and, separately, by geographical area, ( $j = 1, \dots, 4$ ). From the BETAMOD simulated true gross incomes we compute the total amount of reported income and the number of taxpayers for the same characteristics.

Then, it is possible to compute two sets of average tax evasion rates by *main* source of income  $i$ :

$$[B.1] \quad \bar{e}_i^S = \frac{\bar{y}_i^S - \bar{y}_i^{S,MEF}}{\bar{y}_i^S}$$

and by geographical area  $j$ :

$$[B.2] \quad \bar{e}_j^A = \frac{\bar{y}_j^A - \bar{y}_j^{A,MEF}}{\bar{y}_j^A}$$

To convert the tax evasion rates by main income source type of taxpayers ( $\bar{e}_i^S$ ) into rates referred to types of income received ( $\bar{e}_j^A$ ), we use the BETAMOD estimated true gross incomes to build a  $4 \times 4$  matrix  $B$ , in which each element is total amount of true gross income of type  $i$  ( $i = 1, \dots, 4$ ) received by taxpayers with main source of income type  $i$  ( $i = 1, \dots, 4$ ). The total amount of unreported income by main source of income type  $i$  is computed as:

$$[B.3] \quad U_i^S = (\bar{y}_i^S - \bar{y}_i^{S,MEF}) N_i^S$$

where  $N_i^S$  is the number of taxpayers with main source of income type  $i$ .

With this information it is possible to compute the tax evasion rates by income source by solving the linear system:

$$[B.4] \quad \begin{bmatrix} B_{EMP,EMP} & B_{PENS,EMP} & B_{IMM,EMP} & B_{SELF,EMP} \\ B_{EMP,PENS} & B_{PENS,PENS} & B_{IMM,PENS} & B_{SELF,PENS} \\ B_{EMP,IMM} & B_{PENS,IMM} & B_{IMM,IMM} & B_{SELF,IMM} \\ B_{EMP,SELF} & B_{PENS,SELF} & B_{IMM,SELF} & B_{SELF,SELF} \end{bmatrix} \begin{bmatrix} \bar{e}_{EMP}^R \\ \bar{e}_{PENS}^R \\ \bar{e}_{IMM}^R \\ \bar{e}_{SELF}^R \end{bmatrix} = \begin{bmatrix} U_{EMP}^R \\ U_{PENS}^R \\ U_{IMM}^R \\ U_{SELF}^R \end{bmatrix}$$

$$\text{so } \bar{e}^R = (\bar{e}_{EMP}^R, \bar{e}_{PENS}^R, \bar{e}_{IMM}^R, \bar{e}_{SELF}^R) = B^{-1}U.$$

The amount of unreported income by source type is:

$$[B.5] \quad U_i^R = \bar{e}_i^R Y_i^R$$

and  $Y_i^R$  is the total amount of type  $i$ 's received income. The amount of unreported income by geographical area is instead:

$$[B.6] \quad U_j^A = \bar{e}_j^A Y_j^A$$

and  $Y_j^A$  is the total amount of area  $j$ 's received income.

From the BETAMOD simulated true gross incomes we compute the total amount of individual incomes by main income source type ( $i = 1, \dots, 4$ ) and by geographical area, ( $j = 1, \dots, 4$ ), obtaining the  $4 \times 4$  matrix  $Y = \{y_{ij}\}$ .

By using matrix  $Y$  and the marginal distribution of unreported income by source type,  $U^R$ , and by geographical area,  $U^A$ , with the use of the RAS technique we first obtain the joint distributions of total unreported income by income source and by area,  $U = \{u_{ij}\}$ , and, secondly, the  $4 \times 4$  matrix of average tax evasion rates,  $\bar{e} = \{\bar{e}_{ij}\}$ , by source type of received income and by geographical area:

$$[B.7] \quad \bar{e}_{ij} = \frac{u_{ij}}{y_{ij}}$$

The matrix  $\bar{e}$  is shown in Table 9.

### B.2 Tax evasion profiles by classes of true gross income

Each average tax evasion rate  $\bar{e}_{ij}$  is then modulated in order to obtain a profile of tax evasion by classes of true gross income, i.e. a vector of tax evasion rates associated with 13 income classes (see Table 8).

Define  $\bar{e}_{ijk}$  as the average tax evasion rate for income class  $k$ , source type  $i$  and area  $j$  with the following function:

$$[B.8] \quad \bar{e}_{ijk} = \frac{k_i^e \bar{e}_{ij}}{1 + (k_i^e - 1) \left( \frac{y_{ijk}}{k_i^y \bar{y}_{ij}} \right)^{z_i}}$$

where:

$y_{ijk}$  = mean gross true of class  $k$ , source type  $i$  and area  $j$ ;

$\bar{y}_{ij}$  = mean gross true of source type  $i$  and area  $j$ ;

$\bar{e}_{ij}$  = average tax evasion rate for source type  $i$  and area  $j$ ;

and the parameters to estimate are:

$k_i^e$  determines the ordinate intercept;

$k_i^y$  determines the level of income for which  $\bar{e}_{ijk} = \bar{e}_{ij}$ ;

$z_i$  determines the curvature of the function.

With this formulation we need to estimate 12 parameters:  $k_i^e, k_i^y, z_i$  with  $i = 1, \dots, 4$ . As we assume that pensions cannot be concealed, the number of parameters reduces to 9. The method used by BETAMOD is a procedure of numeric optimization that assigns randomly the value of the 9 parameters and choose the best combination that minimize the distance function

$$[B.9] \quad D = \sum_k |Y_k^{MEF} - Y_k^{BETAMOD}|$$

where  $Y_k^{MEF}$  and  $Y_k^{BETAMOD}$  are respectively the official returns and the BETAMOD total amount of reported income by classes.

The profiles obtained are shown in Figure 8.

### B.3 Assignment of individual tax evasion rates

The average tax evasion rate  $\bar{e}_{ijk}$  (for the  $i$ -th income source type, the  $j$ -th geographical area and the  $k$ -th class of true gross income) is defined as the ratio between the unreported income  $U_{ijk}$  and the true income  $Y_{ijk}$  of the cell:

$$[B.10] \quad \bar{e}_{ijk} = \frac{U_{ijk}}{Y_{ijk}}$$

And can be seen as the product:

$$[B.11] \quad \bar{e}_{ijk} = \frac{U_{ijk}}{Y_{ijk}} = \frac{U_{ijk}}{Y_{Eijk}} \frac{Y_{Eijk}}{Y_{ijk}} = \bar{e}_{Eijk} H_{Yijk}$$

where:

$Y_{Eijk}$  is the total amount of tax evaders' income in cell  $i, j, k$

$\bar{e}_{Eijk} = \frac{U_{ijk}}{Y_{Eijk}}$  is the average tax evasion of tax evaders in cell  $i, j, k$

$H_{Yijk} = \frac{Y_{Eijk}}{Y_{ijk}}$  is the share of tax evaders income in cell  $i, j, k$

The values of  $\bar{e}_{Eijk}$  and  $H_{Yijk}$  are unknown, but we know their product  $\bar{e}_{ijk}$  and their maximum value (i.e. 100%). In the absence of further information, we assume that the two values are equal, so:

$$[B.12] \quad H_{Yijk} = \bar{e}_{Eijk} = \sqrt{\bar{e}_{ijk}}$$

For instance, if the average tax evasion rate in a cell is 0.25, then we assume that  $H_{Y_{ijk}} = \bar{e}_{E_{ijk}} = \sqrt{0.25} = 50\%$ , i.e. tax evaders own the 50% of the true gross income in the cell and that their tax evasion rate is 50%.

To assign individual tax evasion in BETAMOD we proceed in the following way:

1. for each value  $\bar{e}_{ijk}$  we compute the two values  $\bar{e}_{E_{ijk}}$  and  $H_{Y_{ijk}}$ ;
2. we randomly assign a probability to be a tax evader to each taxpayer in the sample (by means of a uniform distribution) and we order taxpayers in decreasing order of probability;
3. starting with the taxpayer with the highest probability, we assign a random tax evasion rate drawn from a *beta* distribution with mean  $\bar{e}_{E_{ijk}}$  and a standard error varying with the mean;
4. we proceed to assign tax evasion rates to taxpayer with lesser probability until we reach the total amount of unreported income of the cell  $U_{ijk}$ .

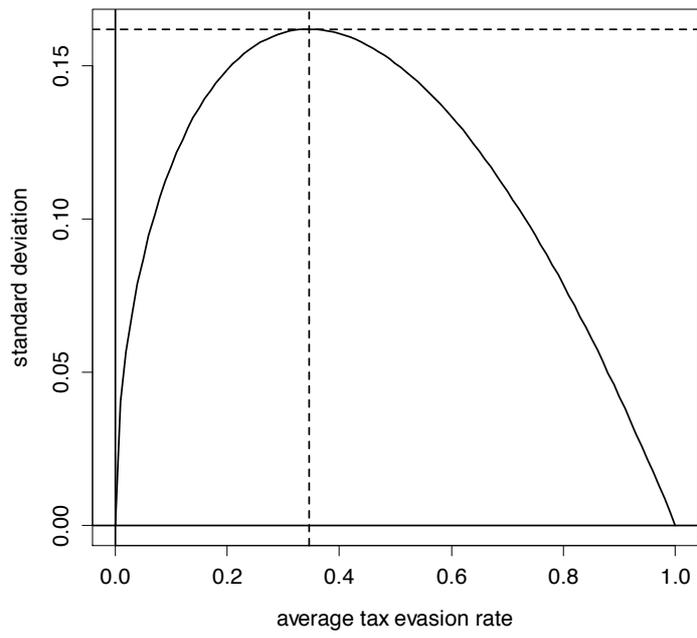
The *beta* distribution used to assign a tax evasion rate  $e_{ijk}$  to the income of source type  $i$  of the

taxpayer  $t$  with characteristics  $j,k$  is then  $e_{ijk} \sim \text{beta}\left(\frac{\theta \bar{e}_{E_{ijk}}}{1 - \bar{e}_{E_{ijk}}}, \theta\right)$ . This *beta* distribution has

expected value equal to  $E(e_{ijk}) = \bar{e}_{E_{ijk}}$  and standard deviation equal to

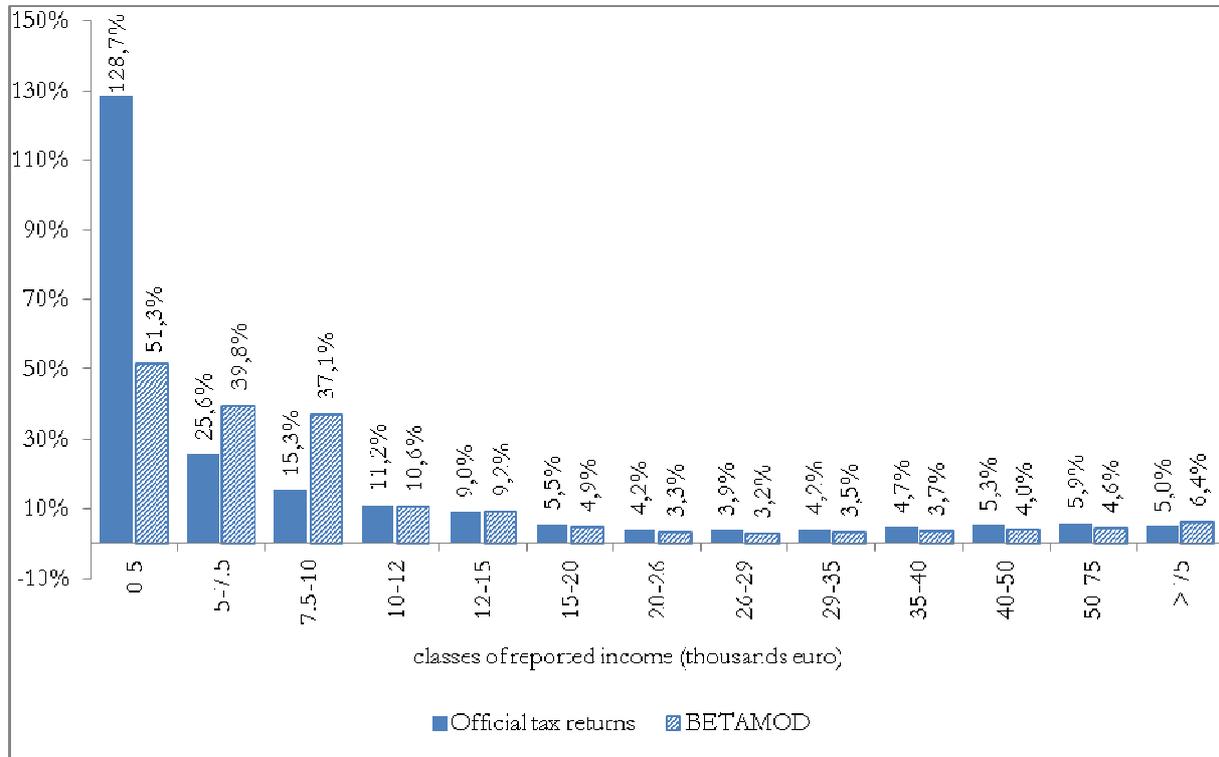
$$sd(e_{ijk}) = \sqrt{\frac{\bar{e}_{E_{ijk}}(1 - \bar{e}_{E_{ijk}})^2}{k + 1 - \bar{e}_{E_{ijk}}}}.$$

The standard deviation is close to zero when there is no tax evasion ( $\bar{e}_{E_{ijk}} = 0$ ) or when all income is concealed ( $\bar{e}_{E_{ijk}} = 1$ ), and is negatively correlated with the parameter  $\theta$ . We assigned to  $\theta$  a value of 5 in order to obtain a maximum value of the standard deviation approximatively equal to 1/6 when the average tax evasion rate is about 1/3 (see figure below).

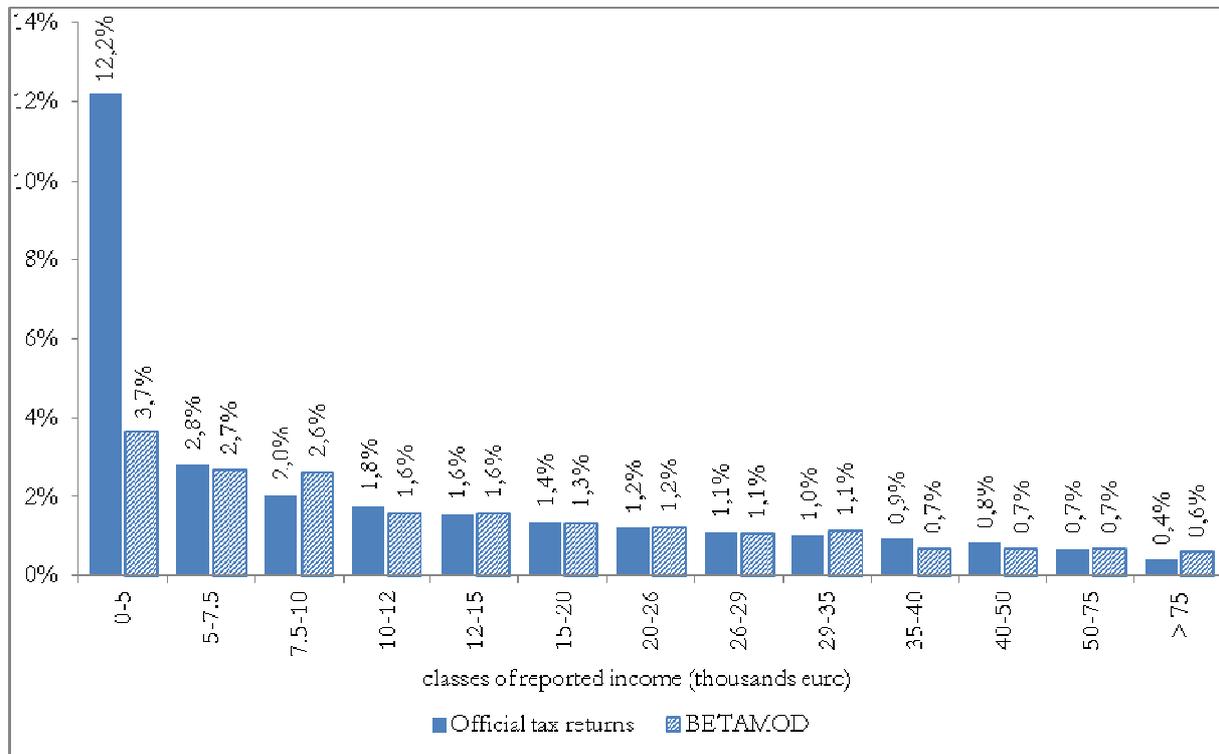


## Appendix C – Incidence of tax reliefs on reported income

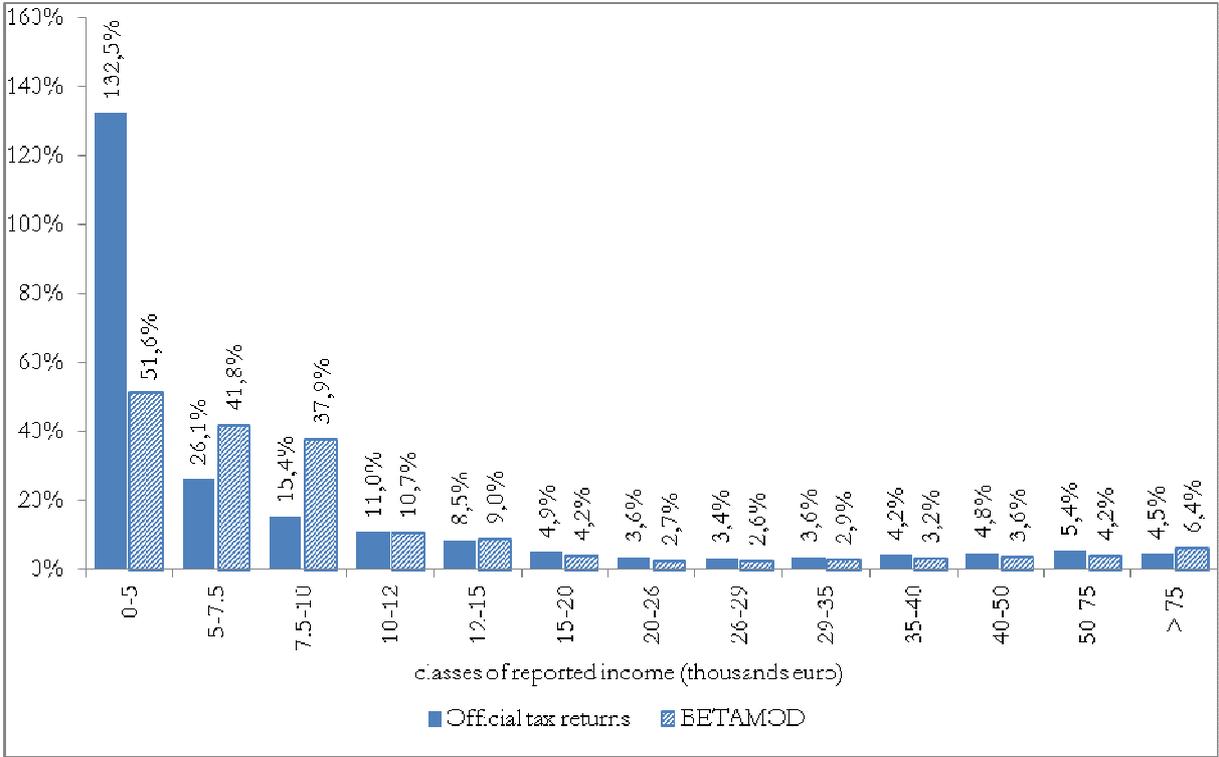
**Figure C.1** Total tax deductions as a proportion of reported income (%)



**Figure C.2** The 19% tax credits as a proportion of reported income (%)



**Figure C.3** Social insurance contributions paid by self-employed individuals as a proportion of reported income (%)



**Figure C.4** The 19% tax credit for healthcare expenses as a proportion of reported income (%)

