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Measuring the Impact of the Crisis on Unemployment and Household Income

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1. Introduction

The current economic crisis has significantly increased unemployment rates and its effect is more persistent than expected, leading to an increase in long term unemployment and inactivity. Among other effects, the experience of unemployment results in a decrease in purchasing power, a loss of human capital, a discouraging effect among the long-term unemployed and the inactive (Berger *et al*., 2009, p. 14) as well as wide-ranging social costs as a worsening of inequality and well-being indicators (Sen, 1997a,b).

The assessment of the costs of unemployment on individuals and households' living conditions is usually carried out using microeconomic data from household surveys that are however issued with delay. Hence, they do not allow for a prompt analysis of the impact of the economic cycle to guide policy makers. In the case of the European Income and Living Conditions Surveys (EU SILC) the data are available with a delay of at least one year and, additionally, we have to consider that the income data refers to the year before the survey (for instance, in the Italian case the last available microdata at the moment of writing this paper are from 2011). To solve this problem we carried out a microsimulation analysis using the European Statistics on Income and Living Conditions Surveys together with the Labour Force Survey (LFS) microdata. Therefore, we propose a methodology based on different sources of microdata that could provide the analysts and the policy makers with a more immediate analysis of the costs of unemployment. This would prove to be extremely useful in a time of high unemployment and budgetary restrictions as the one in which we find ourselves in today.

The microsimulation technique developed in this paper is based on the imputation of transition probabilities and simulated income. Unlike other techniques such as the re-weighting approach (Estevao and Särndal, 2006), the microsimulation technique adopted here allows us to take into account the changes occurred in the composition of the unemployed. Our proposal also differs from the EU EUROMOD. This microsimulation model simulates individual and household tax liabilities and benefit entitlements according to the policy rules in place in each member state of the EU. It is a static model in the sense that the arithmetic simulation of taxes and benefits abstracts from potential behavioural reactions of individuals and the socio-demographic characteristics of the population are assumed to be fixed over time (Sutherland and Figari, 2013). Nevertheless, Navicke *et al.* (2013 a and b) expanded standard EUROMOD elements with additional adjustments to the input data needed to capture changes in the employment characteristics of the population over time. Their purpose was to present and validate an application of the microsimulation method to estimate current at-risk-of-poverty rates in a comparable and consistent way across the EU. As previously mentioned, we propose an alternative technique based on the imputation of transition probabilities and simulated income to take into account not only the increase in unemployment, but also major changes in its composition in assessing the impact of shocks on income and poverty.

To test the validity of the proposed methodology we apply it to Italy, a European country severely hit by the crisis. We focus on the Italian economy since this country is a member of the Eurozone and its labour market has particular structural characteristics (Karamessini, 2008, and Verashchagina and Capparucci, 2014): a high degree of inflexibility in wage determination, rigidity in hiring and firing practices, very low achievement in terms of female labour-force participation (World Economic Forum, 2010) and a strong duality between fixed-term and open-ended contracts. The country has an employment protection system corresponding to the Mediterranean model that is characterized by a rather low coverage of unemployment benefit (Sapir, 2005) moreover, the wide use of temporary contracts in hiring young workers to avoid the much higher dismissal costs of permanent contracts coupled with the deep recession, have resulted in a youth unemployment rate standing well over the European average.

The remainder of the paper is organised as follows. In Section 2 we introduce the methodology that will be used to microsimulate the effect of the crisis on income distribution and income poverty in Section 3 by relying on European surveys. In order to check its validity, we do progress with its application to Italy in Section 4. The final section will offer conclusions.

2. The microsimulation technique: our nowcasting proposal

Economic policy making needs ex-ante and ex-post evaluation. The different methodologies available in order to match these challenges are usually classified in two groups: microeconomic techniques, based mostly on incidence analyses and econometric evaluation approaches in partial equilibrium settings; and macro-micro techniques, which, with different degrees of integration, combine macro and micro modelling frameworks, usually in a general equilibrium context (Bourguignon *et al.*, 2008).

The first set of techniques, with origin in the public finance literature and widely reviewed in Bourguignon and Pereira da Silva (2003), has been applied primarily to analyze the incidence of tax and public spending. So, most of the literature on microsimulation techniques simulate the effect of policy reforms and the impact of economic shocks that lead to a projected change in income and hence in poverty at the household level (see, for example, Baldini and Ciani, 2011).

It is true that pure microeconomic techniques cannot consider the poverty impacts of choosing, implementing, or altering macroeconomic policies (the policy mix of fiscal and monetary policies, or the labour market regulation, for example). Moreover, micro techniques may measure the overall financial cost of a specific program; however, they stop short of "feeding" this cost to a macro model and thus they cannot gauge what kind of macro repercussions (fiscal or growth, for instance) such an intervention may have (Bourguignon *et al.*, 2008). Nevertheless, these approaches are of special interest in nowcasting [1] (Immervoll *et al.*, 2006), that is, estimating current indicators using data on the past income distribution combined with other information which can refer to macroeconomic statistics, as in Navicke *et al.* (2013 b). The latter combine macro-level statistics and the EU tax-benefit microsimulation model EUROMOD to estimate (nowcast) the current poverty rate for the EU countries. They adjust the input data supplied to EUROMOD in order to capture changes in the employment characteristics of the population over time. Hence, they overcome a EUROMOD's shortcoming: it is a static model, as previously mentioned and therefore, it does not capture changes in demographic or labour market characteristics as microsimulation calibration or reweight approaches.

The reweighting techniques allow researchers to use auxiliary information on the changes that occur in the population to reweight their data in order to adjust the sample distribution to the new scenario, for example, a new unemployment rate, but preserving the sample distribution with regard to other sociodemographic variables [2]. So, this method has been known a "static ageing" (Immervoll *et al.*, 2005). Another method of adjusting micro-data is explicitly simulating the transitions between states in order to introduce an element of dynamic change into the static microsimulation approach (Navicke *et al.*, 2013 a). Taking into account rapid changes in some characteristics of the population, like the employment status (Jenkins *et al.*, 2013), is particularly important in the prompt assessment of the impact of shocks as an economic crisis given its likely income distributional impact. On this regard taking into account the effect of the economic crisis on unemployment one should consider not only its increase but also the changes in its composition.

Our microsimulation technique is based on the imputation of transition probabilities in order to take into account the changes that the individuals have experienced in their labour market statuses at the current crisis. This permits us to simulate new incomes for individuals and to nowcast the impact of the crisis on income distribution and poverty by overcoming the lack of data derived from the long delay in the publication of microeconomic data from households' surveys.

We assume that micro-data on socioeconomic characteristics of an individual are available in two different surveys, A and B, published in different time. Let us suppose that Survey A supplies the employment status of the individuals at time (t), whereas survey B provides this status with reference to a lagged time (j). So, survey B allows us to observe such status at t-j moment. Moreover, let us suppose that income data are only available in Survey B, at time t-j . Our aim is nowcasting income at time t.

In general terms our technique can be described in three stages (in the next section we will split these three stages into 6 steps in order to provide a better comprehension of the procedure applied to the nowcasting of income distribution and poverty).

The first stage is the estimation of the individual's employment status at the moment t by using survey A. For this purpose, probit models can be applied by using a set of regressors on the socioeconomic characteristics of individuals that are common across the two data sources. We obtain, in this way, the probability of being in a given employment status for an individual according to his socioeconomic characteristics. The use of a multivariate econometric estimation of the probability of each individual labour market transition provides us a better prediction than the strata-based approach (Fernandez Salgado *et al.*, 2012; Avram *et al.*, 2011).

In stage 2, these probit estimations are imputed into the individuals of survey B whose data refers to *t-j*. In this way, we simulate the employment status of the individuals of sample B in *t*. By using these imputed probabilities we obtain probability thresholds according to the relative change in employment status within the strata following survey A statistics during the period analysed. This will be used to simulate the different transitions (e.g. from employment to unemployment, from unemployment to employment, etc.).

In the third stage, using survey B we generate the new income distribution and predict the new socioeconomic indicators at the moment *t*. As we explain in the following section, we apply our approach to EU-SILC survey and Labour Force Survey data in order to nowcast the prompt impact of the changes of labour market on income distribution and poverty.

Our procedure is different from that of other authors. For example, Baldini and Ciani (2011) randomly select the individuals that change their unemployment status. Our technique differs also from Navicke *et al.* (2013 a and b). In a first stage, these authors account for labour market changes and compute different transitions between labour market states of the individuals by using the Labour Force Survey. Then, the income of the observations that have experienced such transitions is re-calculated by utilizing EUROMOD. Secondly, EUROMOD is used again for simulating tax-benefit policies and update household incomes. In a third step, a calibration approach is applied to correct the deviations of the at-risk-of poverty rate calculated using the income simulated by EUROMOD with respect to the rate provided by Eurostat which is obtained on EU SILC data [3]. We use the Labour Force Survey data to obtain the transitions probabilities that will be imputed into EU SILC. After that, we adjust the EU SILC income data [4] of the individuals that have experienced changes in their employment status in the way explained in Section 3.

Our approach also differs from Immervoll *et al.* (2006) as they used EUROMOD static microsimulation by assuming that the characteristics of the new unemployed are the same as those of the existing unemployed and reweight the existing populations to increase the importance of households containing an unemployed person.

3. Implementation of the microsimulation approach: estimating the impact of the crisis on income distribution by using EU SILC & Labour Force Survey data

EU-SILC data provide detailed individual and household socioeconomic characteristics that must be taken into account when analysing the broad impact of the economic crash. However, these data are released with a delay period that does not allow for the prompt assessment of the impact of shocks. Therefore, this survey allows us to exemplify our microsimulation proposal for nowcasting the impact of crisis on income and poverty. To do this, we rely on the Labour force surveys which make employment status data available without a long delay though they do not provide information on income. Therefore, Labour Force Survey data can be considered as our previously named Survey A in the simulation approach outlined in Section 2 and EU SILC will act as our previously named Survey B .

Let us go through each step in the simulation and imputation procedure explained above including details of the different employment conditions, income and benefits:

1. Labour Force Survey data available at the moment t allows to detect the employment status of an individual i at t-1 also. Therefore, the employment status of i in t given its employment condition in t-1 can be estimated by using the Labour Force Survey data and multivariate analyses. For this purpose, we define the variable

$$u_{i,t} = \begin{cases} 1 \text{ if } i \text{ is unemployed in } t \text{ and was employed in } t-1, \; i = 1,\ldots,n \\ 0 \text{ otherwise} \end{cases}$$

The probability of becoming unemployed in t, having been employed in t-1 is calculated by using the probit model

$$prob\,(u_{i,t} = 1) = \Phi(\mathbf{X}_{i,t}^{LFS}\,\boldsymbol{\beta}_i') \qquad (1)$$

where $\mathbf{X}^{LFS}$ is the vector of socioeconomic and demographic variables contained in the Labour Force Survey that affect this probability and $\boldsymbol{\beta}$ is the row vector of coefficients of the probit model. In our empirical application the variables included in the models estimated in this step are harmonised to those available in the EU-SILC data set.

Similarly we have estimated the following probabilities by using Labour Force Survey data:

- unemployed at year *t* and inactive at *t*-1;
- employed at year *t* and unemployed at *t*-1;
- inactive but searching for a job or available to accept a job at *t*
- probability of being on the wage supplementation fund and employed at *t*

2. The estimated probabilities in *t* are, then, imputed into the EU SILC sample, dated at *t-j*, in order to reproduce the *t* employment scenario. That is

$$prob\ \hat{u}_{i,t-j} = \Phi(\mathbf{X}_{i,t-j}^{SILC}\,\hat{\boldsymbol{\beta}}_i') \qquad (2)$$

where $prob\ \hat{u}_{i,t-j}$ defines the EU SILC individual probability to become unemployed under the scenario described by the LFS dated at *t*.

Note that $\mathbf{X}^{SILC}$ and $\mathbf{X}^{LFS}$ contain exactly the same set of variables. For this purpose we had to recode some variables for the sake of conformity.

3. In this step we define the threshold to simulate the change in the employment status.

In order to simulate the transition from employment to unemployment we define a probability threshold (p) by using the estimated $prob\ \hat{u}_{i,t-j}$.

Let α be the percentage of individuals who became unemployed at *t*. Hence, $1-\alpha$ is the percentage of individuals that have not experienced this transition. This information is provided by the LFS.

Let us assume that $F_{i,t-j}$ is the cumulative probability density function of a Normal distribution. The value of $prob\ \hat{u}_{i,t-j}$ associated with $F_{i,t-j} = 1-\alpha$ provides a threshold p that is equal to the probability of moving from employment to unemployment.

Using p we define the dummy variable:

$$simU_{i,t-j} = \begin{cases} 1 \text{ if } i \text{ is employed and } prob\ \hat{u}_{i,t-j} > p \\ 0 \text{ otherwise} \end{cases} \qquad (3)$$

The procedure described above is used to simulate the following employment status considered in the empirical application:

- unemployed in *t* and employed at *t-j*
- unemployed in *t* and inactive at *t-j*
- employed in *t* and unemployed at *t-j*
- inactive in t-j but searching a job or available to accept it at *t*
- on the wage supplementation fund at *t* and employed at *t-j*

4. In this step we estimate the unemployment benefit to be imputed to those who experience the transition to unemployment and the wage to be imputed to those who experience the transition to employment. This estimation is carried out by using EU SILC data at *t-j*.

The net unemployment benefit is estimated by using equations (4) and (5), in which Heckman's two-step model (1979) was used to correct for the non-random selection into unemployment.

Let

$$b_{i,t-j} = Z_{i,t-j}\beta_{i,t-j} + \varepsilon_{i,t-j} \qquad \varepsilon_{i,t-j} \sim \mathrm{N}\left(0, \sigma_\varepsilon^2\right) \tag{4}$$

where $b_{i,t-j}$ is the net unemployment benefit, which is observed only among individuals who are unemployed according to the information provided by the EU SILC *i.e.* for those individuals whose $U_{i,t-j} = 1$, that is, individuals in unemployment at *t-j*. The estimate of the net unemployment benefit has therefore been corrected by individuals selection in unemployment using the expression

$$E\left\lfloor b_{i,t-j} \mid Z_{i,t-j}, U_{i,t-j} = 1 \right\rfloor = Z_{i,t-j}\beta_i + \theta\lambda_{i,t-j} = \hat{b}_{i,t-j} \tag{5}$$

in which $\lambda_{i,t-j}$ is included in the regression to correct for the non-random selection of the unemployed in the net unemployment benefit equation. The covariates $Z_{i,t-j}$ include the individual's age, marital status, education level, status of health, presence and age of children.

Net wages ($w_{i,t-j}$) for those who were unemployed and, according to the simulation, appear to be employed are estimated using Heckman's selection model (equations 6 and 7) for women in order to account for their selection into employment, and by OLS for employed men.

$$w_{i,t-j} = B_{i,t-j}\mu_{i,t-j} + \varepsilon_{i,t-j} \qquad \varepsilon_{i,t-j} \sim \mathrm{N}\left(0,\sigma_{\varepsilon}^{2}\right) \tag{6}$$

$$E\left[w_{i,t-j} \mid B_{i,t-j}, U_{i,t-j} = 1\right] = B_{i,t-j}\mu_{i,t-j} + \theta\lambda_{i,t-j} \tag{7}$$

$\lambda_{i,t-j}$ = Heckman's term to correct for non-random selection

The covariates $B_{i,t-j}$ affecting wages are age, marital status, education level, status of health, presence and age of children and region.

5. Simulated individual *i*'s income at time *t* has been obtained from EU SILC individual income at *t-j* taking into account the loss of income and/or the gain connected to each household members' simulated employment condition as in equations (8-12).

$$y_{i,t}^{s} = [y_{i,t-j} - w_{i,t-j} + \hat{b}_{i,t-j} \mid (sim\, U_{i,t} = 1 \text{ and } E_{i,t-j} = 0)] \tag{8}$$

$$y_{i,t}^{s} = [y_{i,t-j} - b_{i,t-j} + \hat{w}_{i,t-j} \mid (U_{i,t-j} = 1 \text{ and } simE_{i,t} = 1)] \tag{9}$$

$$y_{i,t}^{s} = [y_{i,t-j} + \hat{w}_{i,t-j} \mid (IN_{i,t-j} = 1 \text{ and } simE_{i,t} = 1)] \tag{10}$$

$$y_{i,t}^{s} = [y_{i,t-j} - w_{i,t-j} \mid (E_{i,t-j} = 1 \text{ and } sim\, IN_{i,t} = 1)] \tag{11}$$

$$y^s_{i,t} = [y_{i,t-j} - 0.20 w_{i,t-j} \mid (sim\ WS_t = 1 \text{ and } sim\ E_{i,t} = 1)] \qquad (12)$$

where

$y^s_{i,t}$ = simulated net individual income

$y_{i,t-j}$ = net household income at *t-j* (as measured in SILC)

$\hat{b}_{i,t-j}$ = net estimated unemployment benefit (as in step 4)

$\hat{w}_{i,t-j}$ = net estimated wage (as in step 4)

$w_{i,t-j}$ = net individual earnings (as measured in SILC)

$U_{i,t-j}$ = dummy taking the value of 1 if the individual is unemployed

$sim\ U_{i,t}$ = dummy variable taking the value of 1 if the individual is defined as unemployed after simulation at *t*

$E_{i,t-j}$ = dummy taking the value of 1 if the individual is employed

$sim\ E_{i,t}$ = dummy variable taking the value of 1 if the individual is defined as becoming employed after simulation

$sim\ WS_{i,t}$ = dummy taking the value of 1 if the individual is defined after simulation as being under wage supplementation fund in Italy

$sim\ IN_{i,t}$ = dummy taking the value of 1 if the individual is defined as being inactive after simulation

Those who are simulated to be unemployed at *t* but were employed at *t-j* have been simulated to gain the estimated unemployment benefit ($\hat{b}_{i,t-j}$) and to lose their labour income at *t-j* (equation 8). Individuals who are simulated to be employed at *t* but were unemployed at *t-j* lose their unemployment benefit at *t* and gain their imputed wage (9). Employed at *t* according to simulation but inactive at *t-j* have been added their imputed wage (10).

Inactive at *t-j* but simulated to be unemployed at *t* do not change income compared to *t-j*. Inactive at *t* according to simulation but employed at *t-j* lost their wage at *t* (11).

In addition, the probability of being under wage supplementation fund at *t* has been estimated and for those who were simulated to be under wage supplementation fund but employed at *t-j* a wage supplementation subsidy at 80% of the former wage (according to the system of wage supplementation fund) has been considered and 20% of their wage at *t-j* has been subtracted accordingly (12).

6. Simulated *t* individuals' incomes for each household's component are then added to obtain household net income. OECD equivalence scale is then used to obtain the equivalised household net income. The new income levels are used to generate poverty indicators.

Finally, the simulated household net equivalised income and poverty rates at *t* are compared to the actual household net equivalised income and poverty rates to validate the methodology adopted.

4. Results of the estimation of the employment status and on the microsimulated equivalised household's income

In order to simulate the effect of the change in employment status on income distribution, as shown in the previous section, we imputed the probability of being unemployed, having been previously employed to each record of IT SILC07 as estimated on the basis of the 2009 third quarter results of the Italian labour force survey data (Tables 1 and 2). To account for gender differences in the likelihood of becoming unemployed, the models are estimated separately for women and men.

[Table 1 - approximately HERE]

Focusing on the results, we find that unlike men, women aged 35 to 39 were more likely to become unemployed in 2009, while this likelihood significantly decreases for both groups among workers over 55. Higher education reduces the likelihood of becoming unemployed, and the probability of becoming unemployed increases by 0.2% for women and 1.2% for men if they live in the South of Italy. Turning to the impact of the type of sector, marginal effects show a 3% increase in the probability of becoming unemployed for males employed in the construction sector and 2% if employed in the estate agency sector. The likelihood of becoming unemployed is higher among blue-collar and unskilled work positions for both men and women. Unlike men, women in scientific and highly-skilled positions show a statistically significant increase of 2% of the likelihood of their becoming unemployed.

[Table 2 - approximately HERE]

Taking into account the higher probability of receiving benefits from the Italian wage supplementation fund during the current crisis, the same set of microdata is used in order to estimate the probability of being employed but part of the wage supplementation scheme. This is a condition not considered as unemployment in the Italian Labour Force Survey but which is found to reduce household income and lead to uncertainty in future labour market conditions. The probability of receiving benefits from the wage supplementation fund (Table A1) does not increase in the South, and it is significantly higher among men in various employment sectors. Indeed, being employed in manufacturing increases the probability of being under the wage supplementation fund by 7% for men and 3% for women.

Italy is characterised by a higher incidence of inactivity among the working-age population (especially women). In order to account for the loss of income connected to being inactive but still searching for a job or available to accept a job, we estimated the probability of being in this condition by gender by using ISTAT LFS 2009 data, and imputed this probability to IT SILC 2007 microdata (Table A2). Apart from very young and older women, the probability of being inactive increased in 2009, decreasing among more educated people (this probability decreases by 4% for women having completed tertiary education and for 2.4% of men with tertiary education), and significantly increases for those living in the South of Italy (by 8% for men and 10% for women). The probability of being inactive is also higher (up by 2%) for mothers of children aged between six and fourteen as there is a low synchronization between schooling hours and normal hours of work.

In order to account for the increase in unemployment rates on entering or re-entering the labour market, we estimated the probability of becoming unemployed having been inactive (Table A3). This probability is higher for individuals under 34 (among men) and 39 (among women) with an increase of 4% for men and women aged

20 to 24. Having a child aged from 6 to 14 increases the likelihood of becoming unemployed if previously inactive by 0.8% in the case of mothers, while living in the South of Italy increases the probability of being unemployed for the previously inactive by 1% for men and 0.8% for women.

We then estimated the probability of becoming employed in the year 2009 having been unemployed one year before (Table A4). Turning to education the probability of entering employment after a spell of unemployment is significantly higher only for women in tertiary education. The youngest and eldest age groups show a reduction in the likelihood of experiencing a shift towards employment. Being married does not increase the probability of becoming employed.

For those simulated to being employed after having been unemployed, we then imputed a labour income as estimated by the Heckman two-step selection model for women and OLS for men. For those who were simulated as being under a wage supplementation fund subsidy the subsidy was imputed as being up to 80% of their former employment income, according to a threshold set by the Italian National Social Security Institute.

For those who were not unemployed according to the IT SILC 2007 survey but – according to the simulation – would have been unemployed in the year 2009, we then imputed an unemployment benefit obtained by the estimation of a two-step Heckman model on IT SILC 2007 data (Table A5) [5]. Unemployment benefits tend to increase with the age of the unemployed (though with a 10% level of significance) in line with a probable higher level of wages connected to seniority in employment. Unemployment benefits, according to the multivariate analysis, tend to be lower for men, which may be connected to the inclusion in the second step of the model of women being more likely covered by unemployment benefits. However, it should be noted that women have a higher likelihood of losing their jobs and becoming inactive, and therefore being left without any unemployment benefit. Wage equations estimated to impute labour income to those who entered employment according to the simulation show the positive effect of higher education on hourly wages, lower wages in the South of Italy both for men and for women and the positive effect of selection into employment on potential wages (Table A6).

To evaluate the microsimulation we then compare actual and simulated median equivalised household's income in year 2009. These results are reported in Table 3 jointly with the standard deviation (Goedemé *et al*, 2013). The actual median equivalised household's income in 2009 is similar to the one obtained by applying our simulation technique. At the national level, the comparison between actual and simulated median of income distribution, referred to the whole population, shows a deviation of 0.41% [6].

[Table 3 - approximately HERE]

Focusing on the poverty rates for the working age population the results of the simulation are in line with the actual results. As shown in Table 4, the simulated poverty rate for men is 17.5% on average and the actual 2009 one is 17.9%. According to simulated data 19.3% of women in working age population are poor and, by using 2009 IT SILC data 20.4% of women in the same age group result poor.

We could interpret the low differences occurring between the simulated and actual values as a good indicator of the usefulness of the proposed methodology in measuring the changes in income distribution and poverty. The possibility to provide these measures before the actual provision of data is particularly relevant in a time of crisis to devise policies able to tackle the effect of the cycle on different groups of the population.

[Table 4 - approximately HERE]

Conclusions

This paper aims at providing a technique able to simulate the impact of job loss on household's income in European countries. The microsimulation has been carried out by using two different sources of data: labour force survey data that are more promptly available to estimate the employment condition in year *t* and the European Statistics on Income and Living Conditions Survey EU SILC for year *t-j*. Nevertheless, the application of this technique can be extended to others surveys.

Individual income has been simulated taking into account the loss of labour income incurred if simulated to be unemployed or inactive in year *t* and the gain in wages for those who were simulated to become employed in *t* in spite of the crisis. The estimated unemployment benefit and – as in Italy where also the wage supplementation fund is at work - a reduction in wages has been computed for individuals who were unemployed or in a wage supplementation scheme.

The microsimulation has been carried out with regards to Italy, a country that has been severely hit by the crisis.

Distinct from other microsimulation techniques the methodology proposed in this paper allows us to take into account behavioural effects and the change in the composition of employment and unemployment. The methodology has been tested by comparing actual and simulated IT SILC data for year 2009. Actual and simulated equivalised household income and poverty rates result similar. This would encourage the use of the suggested methodology to anticipate the effect of the economic cycle on household's income in order to adopt more focussed policies to counteract poverty.

Notes

1. Navicke *et al.* (2013 a) highlighted the difference between nowcasts and forecasts. Nowcasts are informed by using macro-economic variables that are available with a short time lag, together with information about current policies. Forecasts must rely on other forecasts, projections or assumptions about the future economic situation and the evolution of policies.
2. The basic theory for calibration is provided by Deville & Särndal (1992) and Creedy (2003). A complete review of the new techniques of the reweighting approach may be found in Estevao and Särndal (2006). An application of this simulation technique may be found in Immervoll *et al*. (2006).
3. Avram and Sutherland (2012) reviewed the reasons why the estimates of both sources differ.
4. Since we obtain the poverty rates by using survey B, we do not require the calibration approach used by Navicke *et al.* (2013 b).
5. We included perceived health status and family composition in terms of presence and age of children in the first step of the estimation, given the expected effect of these variables on unemployment probability being higher than on the level of unemployment benefit as an identifying assumption.
6. Simulating equivalised household income, by using the reweighting approach, instead, did not provide satisfactory results: reweighting the sample of 2007 so that it would reflect the unemployment rates of 2009, would lead to simulate an equivalised household income just equal to 15,035.33, therefore underestimating the actual income in 2009.

References

Avram S., H. Sutherland, I., Tasseva and A. Tumino (2011), "Income protection and poverty risk for the unemployed in Europe", Research Note 1/2011 of the European Observatory on the Social Situation and Demography, European Commission. http://www.socialsituation.eu/WebApp/ResearchNotes.aspx

Avram S. and H. Sutherland (2012), "Baseline results from EUROMOD: 2006-2009 policies" EUROMOD Working Paper EM1/12 Colchester: ISER, University of Essex.

Baldini, M. and E. Ciani (2011), "Inequality and Poverty during recession in Italy", *Politica Economica*, No.3, pp. 297-322.

Berger, J., Keuschnigg, C., Keuschnigg, M., Miesse, M., Strohner, L., and R. Winter-Ebner (2009), "Modelling of Labour Markets in the European Union. Final Report*", DG EMPL/D/1* ref. No. VC/2007/0344 .

Bourguignon, F., and L. A. Pereira da Silva, (Eds) (2003), *The Impact of Economic Policies on Poverty and Income Distribution: Evaluation Techniques and Tools,* The World Bank, Washington, D.C..

Bourguignon, F., Bussolo, M. and Pereira da Silva, L. (2008), "Evaluating the impact of macroeconomic policies on poverty and income distribution", Bourguignon, F., Bussolo, M. and Pereira da Silva, L. (Eds) *The impact of macroeconomic policies on poverty and income distribution: Macro-micro evaluation techniques and tools*, The World Bank, Washington, D.C., pp. 1-26.

Creedy, J. (2003), "Survey Reweighting for Tax Microsimulation Modelling"*, New Zealand Treaury Working Paper* 03/17.

Deville, J.C. and C.E. Särndal (1992), "Calibration estimators in survey sampling", *Journal of the American Statistical Association,* Vol.87 No.418, pp. 376–382.

Estevao, J.M. and C.E. Särndal (2006), "Survey Estimates by Calibration on Complex Auxiliary Information", *Journal of the American Statistical Association,* Vol. 74 No. 2, pp.127–147.

Fernandez Salgado M., F. Figari, H. Sutherland and A. Tumino (2012), "Welfare compensation for unemployment in the Great Recession" *EUROMOD Working Paper EM3/12*, ISER, University of Essex, Colchester.

Goedemé T., Van den Bosh K., Salamauskante L., and Verbist G. (2013), "Testing the Statistical significance of Microsimulation results: A Plea", *International Journal of Microsimulation*, Vol.6 No. 3, pp. 50-77.

Heckman, J. J., (1979) "Sample Selection Bias as a Specification Error", *Econometrica*, Vol. 47 No. 1, pp. 153-161.

Immervoll, H., Levy, H., Lietz, C., Mantovani, D. and H. Sutherland (2006), "The sensitivity of poverty rates to macro-level changes in the European Union", *Cambridge Journal of Economics*, 30, pp.181–199.

Immervoll H., K. Lindstrom, E. Mustonen, M. Riihela, and H. Viitamäki (2005), "Static Data 'Ageing' Techniques. Accounting for Population Changes in Tax-Benefit Microsimulation Models", *Euromod Working Paper* EM5/05, ISER, University of Essex, Colchester.

Jenkins, S. P., Brandolini, A., Micklewright, J., and Nolan, B. (2013), *The great recession and the distribution of household income*, Oxford University Press, Oxford.

Karamessini, M. (2008), "Still a Distinctive Southern European Employment Model?", *Industrial Relations Journal*, Vol. 39 No.6, pp. 510-531.

Navicke, J., Rastrigina, O., and Sutherland, H., (2013 a), "Using EUROMOD to nowcast poverty risk in the European Union", Eurostat Methodologies and Working Papers. Luxembourg: Publications Office of the European Union.

Navicke, J., Rastrigina, O., and Sutherland, H., (2013 b), "Nowcasting Indicators of Poverty Risk in the European Union: A Microsimulation Approach", *Social Indicators Research*, online first: 1-19. doi: 10.1007/s11205-013-0491-8.

Sapir, A., (2005) *Globalisation and the reform of European Social Models. Background document for the presentation at ECOFIN Informal Meeting in Manchester, 9 September 2005.* Bruegel, Brussels, 2005.

Sen, A., (1997 a) 'Inequality, unemployment and contemporary Europe', *International Labour Review*, Vol.136 No. 2, pp.155-171, 1997a.

Sen, A. (1997 b) "The Penalties of Unemployment", *Temi di discussione*, 307, Banca d'Italia, Rome.

Sutherland, H and Figari, F., (2013), "EUROMOD: The European Union Tax-Benefit Microsimulation Model", *EUROMOD Working Paper No. EM 8/13*, 2013

Verashchagina, A. and Capparucci, M. (2014), "Living through the crisis in Italy: the labour market experience of men and women", in M.Karamessini and J.Rubery (Eds), *Women and Austerity. The economic crisis and the future for gender equality*, Routledge, New York, pp. 248-269.

World Economic Forum (2010), *The Global Competitiveness Report 2010-2011*. World Economic Forum, Geneva.

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TABLES

Table 1 – Unemployment rates in Italy and Eurozone in years 2007 and 2009 by different groups of the population.

	2007		2009	
	Euro zone	Italy	Euro zone	Italy
Total	7.4	6.1	9.5	7.9
Breakdown by sex				
Males	6.6	4.9	9.3	6.9
Females	8.5	7.9	9.7	9.3
Breakdown by age				
15 to 24 years	15.0	20.3	19.7	25.4
25 to 49 years	6.7	5.8	8.9	7.4
50 to 64 years	6.1	2.5	6.8	3.7
Breakdown by highest level of education				
Pre-primary, primary and lower secondary	10.5	7.3	15.1	9.6
Upper secondary and post-secondary non-tertiary	7	5.6	8.5	7.3
Tertiary education	4.4	4.4	5.4	5.6

Source: Eurostat -Labour Force Survey

Table 2 – Probability of becoming unemployed in 2009 III quarter in Italy

Variables	Men		Women	
	Coeff.	Marg. at means	Coeff.	Marg. at means
15-19	-0.875**	-0.019	-0.641**	-0.008
	(6.38)		(4.59)	
20-24	0.012	0.001	0.035	0.001
	(0.17)		(0.42)	
25-29	0.049	0.002	0.062	0.002
	(0.78)		(0.88)	
30-34	0.013	0.001	0.069	0.002
	(0.21)		(1.08)	
35-39	0.079	0.004	0.185**	0.005
	(1.51)		(3.31)	
55-59	-0.149*	-0.006	-0.443**	-0.007
	(2.32)		(4.41)	
60-64	-0.458**	-0.014	-0.695**	-0.009
	(5.33)		(5.54)	
Tertiary	-0.220**	-0.008	-0.163*	-0.003
	(2.72)		(2.03)	
High school	-0.113**	-0.005	-0.175**	-0.004
	(2.69)		(3.22)	
Agriculture	-0.039	-0.002	-0.232	-0.004
	(0.42)		(1.95)	
Manufacturing	0.299**	0.016	0.232**	0.007
	(4.20)		(2.92)	
Construction	0.473**	0.031	0.203	0.006
	(6.35)		(1.06)	
Trade	0.265**	0.015	0.138	0.004
	(3.37)		(1.76)	
Hotel	0.262*	0.015	0.202*	0.006
	(2.34)		(2.33)	
Transport	0.291**	0.017	-0.072	-0.002

	(2.99)		(0.49)	
Financial	0.292*	0.017	0.136	0.004
	(2.22)		(0.85)	
Real estate	0.335**	0.020	0.052	0.001
	(3.81)		(0.61)	
Other sectors	0.223*	0.012	-0.000	0.000
	(2.26)		(0.00)	
Scientific and highly skilled positions	0.044	0.002	0.553**	0.023
	(0.38)		(4.09)	
Technical positions	0.041	0.002	0.518**	0.019
	(0.47)		(5.23)	
White-collar	0.223*	0.012	0.642**	0.028
	(2.27)		(6.11)	
Skilled in Trade and Services	0.222*	0.012	0.771**	0.036
	(2.49)		(8.10)	
Craft. skilled blue-collar. agric.	0.317**	0.017	0.757**	0.040
	(3.97)		(6.37)	
Machine operators and semiskilled blue collar	0.175	0.009	0.699**	0.036
	(1.87)		(5.49)	
Unskilled	0.567**	0.042	0.899**	0.052
	(6.57)		(9.44)	
Army	-0.520*	-0.014		
	(2.30)			
South	0.241**	0.012	0.100*	0.002
	(6.92)		(2.40)	
Married	-0.223**	-0.010	-0.298**	-0.007
	(5.35)		(6.70)	
Self-employed collaborator	-0.260**	-0.010	-0.083	-0.002
	(5.13)		(1.21)	
Constant	-2.210**		-2.482**	
	(29.20)		(30.64)	
Observations	47359		49455	

Robust z statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Our elaborations on ISTAT Labour Force Survey Data 2009

Table 3 - Descriptive statistics on actual and simulated equivalized disposable household income in 2009

	Median	S.D.
Actual	16327	12867
Simulated	16260	12592
% difference actual-simulated	0.41%	

Source: Our elaborations on IT SILC 2007 simulated microdata and IT SILC 2009.

Table 4 - Descriptive statistics on actual and simulated

poverty rates in Italy - working age population in 2009

	M	F	M+F
Actual	0,175	0,193	0,184
SD	*0,38*	*0,395*	*0,387*
obs	14,999	15,492	30,491
Simulated	0,179	0,204	0,192
SD	0,384	*0,403*	*0,394*
obs	16,734	17,228	33,962

Source: Our elaborations on IT SILC 2007 simulated microdata and IT SILC 2009.

Appendix

Table A1 – Probability of being in the wage supplementation funds scheme

	Men		Women	
	coeff	Marginal eff. at means	coeff	Marginal eff. at means
15-19	-0.605	-0.002		
	(1.59)			
20-24	-0.194	-0.001	-0.332	0.000
	(1.51)		(1.32)	
25-29	-0.351**	-0.001	-0.432**	0.000
	(3.23)		(2.82)	
30-34	0.003	0.000	-0.099	0.000
	(0.03)		(0.99)	
35-39	0.044	0.000	-0.229*	0.000
	(0.61)		(2.06)	
55-59	-0.055	0.000	-0.198	0.000
	(0.65)		(1.62)	
60-64	-0.450**	-0.001	-1.052**	-0.001
	(3.03)		(3.07)	
Tertiary	0.042	0.000	-0.024	0.000
	(0.29)		(0.13)	
High school	0.042	0.000	0.090	0.000
	(0.76)		(1.01)	
Energy Industry and Extraction	0.638	0.008	0.410	0.001
	(1.88)		(1.22)	
Manufacturing	1.939**	0.069	1.554**	0.027
	(7.35)		(6.55)	
Construction	1.182**	0.027		
	(4.27)			
Trade	1.420**	0.046	1.025**	0.008
	(5.25)		(3.68)	

Hotel	0.149	0.001	0.274	0.001
	(0.39)		(0.78)	
Transport	0.924**	0.016	1.060**	0.011
	(3.22)		(3.80)	
Real estate	1.094**	0.026	0.819**	0.005
	(3.82)		(3.13)	
Other sectors	0.625	0.008	0.329	0.001
	(1.77)		(0.96)	
Scientific and highly skilled positions	0.093	0.001	0.213	0.000
	(0.30)		(0.49)	
Technician positions	0.452	0.004	0.239	0.001
	(1.62)		(0.70)	
White collar	0.536	0.005	0.266	0.001
	(1.81)		(0.76)	
Skilled in Trade and Services	0.427	0.004	0.098	0.000
	(1.42)		(0.25)	
Craft, skilled blue-collar	0.565*	0.005	0.569	0.002
	(2.00)		(1.60)	
Machine operators and semiskilled	0.807**	0.011	0.723*	0.004
	(2.84)		(2.02)	
Unskilled	0.514	0.005	0.359	0.001
	(1.70)		(0.99)	
South	0.018	0.000	-0.009	0.000
	(0.31)		(0.11)	
Married	0.048	0.000	0.047	0.000
	(0.76)		(0.61)	
Constant	-4.129**		-3.658**	
	(11.61)		(17.70)	
Observations	35514		39447	

Robust z statistics in parentheses

* significant at 5%; ** significant at 1%

Source: Our elaborations on ISTAT Labour Force Survey Data 2009

Table A2 – Probability of being inactive but searching for a job or being available to work in Italy - year 2009

Variables	Men		Women	
		Marg. eff.		Marg. eff.
	Coeff .	at means	Coeff .	at means
15-19	0.190**	0.021	-0.149**	-0.020
	(4.23)		(3.26)	
20-24	0.602**	0.086	0.307**	0.054
	(14.17)		(7.77)	
25-29	0.465**	0.060	0.335**	0.060
	(10.52)		(8.63)	
30-34	0.268**	0.030	0.234**	0.039
	(6.08)		(6.47)	
35-39	0.016	0.002	0.178**	0.029
	(0.34)		(5.04)	
55-59	-0.072	-0.006	-0.377**	-0.045
	(1.48)		(8.25)	
60-64	-0.101	-0.009	-0.649**	-0.066
	(1.91)		(12.33)	
Tertiary	-0.312**	-0.024	-0.359**	-0.044
	(6.64)		(9.93)	
High school	-0.279**	-0.025	-0.222**	-0.032
	(9.89)		(8.83)	
South	0.675**	0.077	0.598**	0.101
	(27.04)		(27.83)	
At least one child 0-3	-0.039	-0.004	-0.054	-0.008
	(0.91)		(1.49)	
At least one child 3-5	0.010	0.001	-0.026	-0.004
	(0.24)		(0.75)	
At least one child 6-14	-0.050	-0.005	0.139**	0.022
	(1.61)		(5.45)	
Constant	-1.891**		-1.499**	
	(58.45)		(58.04)	
Observations	47359		49480	

Robust z statistics in parentheses

* significant at 5%; ** significant at 1%

Source: Our elaborations on ISTAT Labour Force Survey Data 2009

Table A3 – Probability of becoming unemployed if inactive

Variables	Men		Women	
	Coeff .	Marg.eff. at means	Coeff .	Marg. eff. at means
15-19	0.298**	0.013	0.122	0.006
	(4.05)		(1.79)	
20-24	0.667**	0.041	0.541**	0.039
	(10.46)		(8.67)	
25-29	0.482**	0.025	0.508**	0.035
	(7.20)		(9.10)	
30-34	0.200**	0.008	0.365**	0.022
	(3.07)		(6.34)	
35-39	0.022	0.001	0.233**	0.012
	(0.30)		(4.00)	
55-59	-0.098	-0.003	-0.499**	-0.015
	(0.99)		(5.00)	
60-64	-0.168	-0.005	-0.930**	-0.021
	(1.53)		(6.70)	
Tertiary	0.045	0.002	0.068	0.003
	(0.74)		(1.32)	
High school	-0.066	-0.002	-0.053	-0.002
	(1.61)		(1.30)	
South	0.371**	0.014	0.169**	0.008
	(10.17)		(5.13)	
Married	-0.408**	-0.014	-0.145**	-0.007
	(7.77)		(3.30)	
At least one child 0-3	-0.054	-0.002	-0.095	-0.004
	(0.92)		(1.69)	

At least one child 3-5	0.039	0.001	-0.018	-0.001
	(0.64)		(0.34)	
At least one child 6-14	0.070	0.002	0.156**	0.008
	(1.39)		(3.87)	
Constant	-2.266**		-2.118**	
	(36.07)		(40.81)	
Observations	47359		49480	

Robust z statistics in parentheses

* significant at 5%; ** significant at 1%

Source: Our elaborations on ISTAT Labour Force Survey Data 2009

Table A4- Probability of becoming employed in 2009 if unemployed in 2008

Variables	Men		Women	
	Coeff.	Marginal eff. at means	Coeff.	Marginal eff. at means
15-19	-0.059	-0.0023	-0.494***	-0.0094
	(0.64)		(3.96)	
20-24	0.551***	0.0369	0.414***	0.0185
	(8.47)		(6.21)	
25-29	0.429***	0.0256	0.502***	0.0242
	(6.73)		(8.56)	
30-34	0.312***	0.0166	0.326***	0.0131
	(5.34)		(5.67)	
35-39	0.198***	0.0095	0.252***	0.0094
	(3.19)		(4.43)	
55-59	-0.356***	-0.0108	-0.542***	-0.0102
	(4.19)		(5.54)	
60-64	-0.594***	-0.0149	-1.182***	-0.0147
	(5.49)		(6.47)	
Tertiary	-0.181***	-0.0064	0.087*	0.0028
	(2.98)		(1.67)	
High school	-0.149***	-0.0059	-0.074*	-0.0022

	(3.66)		(1.67)	
South	0.343***	0.0158	0.080**	0.0024
	(9.44)		(2.13)	
Married	-0.057	-0.0023	-0.157***	-0.0048
	(1.27)		(3.67)	
Constant	-2.197***		-2.143***	
	(41.10)		(40.11)	
Observations	47,359		49,480	

Robust z statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Our elaborations on ISTAT Labour Force Survey Data 2009

Table A5– Net unemployment benefit – Heckman two step estimation

	Un.Benefit	Unemployed
Age	0.198	-0.080**
	(1.75)	(15.67)
Age squared	-0.002	0.001**
	(1.52)	(8.98)
South	-0.008	0.093
	(0.04)	(1.91)
Man	-0.362*	0.001
	(2.00)	(0.02)
Married	0.336	0.094
	(1.52)	(1.01)
Separated or divorced	0.029	0.109
	(0.08)	(1.03)
Widow	0.423	-0.392
	(0.41)	(1.92)
Secondary	0.435	-0.338**
	(0.84)	(5.04)
High School	0.441	-0.481**
	(0.66)	(6.43)
Tertiary	-0.148	-0.591**

	(0.18)	(5.92)
Chronic ill		0.186
		(1.82)
Presence of children aged 0-5		-0.051
		(0.48)
Presence of children aged 6-14		-0.005
		(0.09)
Presence of children aged 15-17		-0.293**
		(2.96)
Constant	3.580**	
	(2.64)	
Observations	33423	33423

Robust z statistics in parentheses

* significant at 5%; ** significant at 1%

Source: Our elaborations on IT SILC 2007

Table A6 - Wage Equations

	Women		Men
Variables	log wage	Employed	log wage
Age	0.0551***	0.261***	0.0455***
	(0.0101)	(0.00789)	(0.00447)
Age squared	-0.000510***	-0.00319***	-0.000406***
	(0.000122)	(9.59e-05)	(5.38e-05)
Married	-0.0115	-0.303***	0.117***
	(0.0213)	(0.0298)	(0.0135)
Presence of children aged 0-5		-0.346***	
		(0.0402)	
Presence of children aged 6-14		-0.381***	
		(0.0323)	
Presence of children aged 15-17		-0.0668*	

		(0.0395)	
High School	0.282***	0.484***	0.164***
	(0.0243)	(0.0277)	(0.0113)
Tertiary education	0.507***	0.558***	0.485***
	(0.0291)	(0.0388)	(0.0212)
Chronic Ill		-0.123***	
		(0.0360)	
South	-0.148***	-0.546***	-0.136***
	(0.0274)	(0.0278)	(0.0126)
Heckman Lambda		0.148***	
		(0.0524)	
Constant	4.049***	-5.352***	4.597***
	(0.247)	(0.150)	(0.0877)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Our elaborations on IT SILC 2007