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Nowcasting: timely indicators for monitoring risk of poverty in 2014-2016

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Nowcasting: timely indicators for monitoring risk of poverty in 2014-2016*

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Abstract

The at-risk-of-poverty rate (AROP) is one of the three indicators used for monitoring progress towards the Europe 2020 poverty and social exclusion reduction target. Timeliness of this indicator is crucial for monitoring of the social situation and of the effectiveness of tax and benefit policies. However, partly due to the complexity of EU-SILC data collection, estimates of the number of people at risk of poverty are published with a significant delay. This paper extends and updates previous work on estimating ('nowcasting') indicators of poverty risk using the tax-benefit microsimulation model EUROMOD. The model's routines are enhanced with additional adjustments to the EU-SILC based input data in order to capture changes in the employment characteristics of the population since the data were collected. The nowcasting method is applied to twenty-seven EU Member States. Median income and AROP rates are estimated up to 2016. The performance of the method is assessed by comparing the predictions with actual EU-SILC indicators for the years for which the latter are available. If nowcasts are unreliable we explain the main reasons behind the differences between the nowcasted and SILC-based indicators. For countries with stable and reliable results we discuss the main drivers behind the nowcasted trends.

JEL: C81, H55, I3

Keywords: Nowcasting, At-risk-of-poverty, European Union, Microsimulation

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1. Introduction

Together with very low work intensity and severe material deprivation, the at-risk-of-poverty indicator is used for monitoring progress towards the Europe 2020 poverty and social exclusion reduction target. The timeliness of this indicator is crucial for keeping track of the effectiveness of policies and the impact of macroeconomic conditions on poverty and income distribution. However, partly due to the complexity of the data collection process, estimates of the number of people at risk of poverty are released by Eurostat with a two years' time lag on average for most countries. In February 2017 estimates of at-risk-of-poverty rate based on 2015 income are only available for one EU country.

This paper employs a method to estimate more timely indicators based on 'nowcasting' which uses data on a past income distribution together with various other sources of information. The paper extends and updates previous work on nowcasting median income and the at-risk-of poverty (AROP) indicator for EU countries (Rastrigina et al., 2016; Leventi et al., 2017). The analysis is expanded to two additional countries not covered previously (Belgium and Slovenia); the timing of projections is extended by one or two additional years; the underlying micro and macro data are updated; and the microsimulation-based methodology is further refined.

Microsimulation models have been widely used for assessing the distributional impact of current and future tax-benefit policy reforms, as well as the impact of the evolution of market incomes, changes in the labour market and in the demographic structure of the population.[1] Using microsimulation techniques based on representative household data enables changes in the distribution of market income to be distinguished and the effects of the tax-benefit system to be identified taking into account the complex ways in which these factors interact with each other (Peichl, 2009; Immervoll et al., 2006). Combined macro-micro modelling has also been used for analysing the impact of macroeconomic policies and shocks on poverty and income distribution.[2]

The present analysis makes use of EUROMOD, the microsimulation model based on EU-SILC data which estimates in a comparable way the effects of taxes and benefits on the income distribution in each of the EU Member States. For the purposes of the nowcasting exercise standard EUROMOD routines, such as simulating policies and updating market incomes, are enhanced with additional adjustments to the input

[1] Some examples include Brewer et al. (2013) for the UK, Keane et al. (2013) for Ireland, Brandolini et al. (2013) for Italy, Matsaganis & Leventi (2014) for Greece and Narayan & Sánchez-Páramo (2012) for Bangladesh, Mexico, Philippines and Poland.

[2] A detailed review is provided in Bourguignon et al. (2008) and Essama-Nssah (2005).

data in order to capture changes in the employment characteristics of the population since the SILC data were collected.

The paper covers twenty-seven EU countries: all except the United Kingdom.[3] The nowcasting method is applied to the latest EU-SILC data incorporated in EUROMOD: this is EU-SILC 2012 (referring to incomes of 2011) for 11 countries, EU-SILC 2014 (referring to incomes of 2013) for 15 countries, and EU-SILC 2015 (referring to incomes of 2014) for one country. Median incomes and AROP rates are estimated up to 2016.

The method is evaluated by comparing nowcasted and official EU-SILC indicators for incomes in the period 2011 to 2014, when both are available. We divide all countries into two groups based on their historical performance: (1) countries with stable and reliable results and (2) countries with unreliable results subject to further investigation and improvement. For the first group, we analyse the main drivers behind the nowcasted trends by disentangling changes in AROP due to policy and employment characteristics. For the second group, we explain the main reasons behind the differences between the nowcasted and SILC-based income poverty trends.

The most important findings can be summarised as follows. With the exception of Luxembourg, median equivalised household disposable incomes in 2016 are significantly different from their 2014 levels. The highest nominal increase in the median in 2014-2016 is predicted in Romania (18.4%). Also the Baltic States are expected to have high increases in median incomes: 18.1% in Estonia, 14.0% in Latvia and 13.9% in Lithuania. These increases are mainly driven by pronounced wage growth accompanied by growth in employment. A reduction in the median (-1.3%) is only expected in Cyprus.

Changes in relative at-risk-of-poverty rate for the total population in 2014-2016 are found to be statistically significant in ten out of twenty-seven EU member states. The countries where relative poverty is predicted to increase the most are Malta (+1.1 ppts) as well as Austria, Belgium, the Netherlands and Finland (between +0.4 and +0.8 ppts). The biggest decreases in the AROP rate are estimated for Poland (-3.6 ppts), followed by Spain (-1.1 ppts), Hungary (-0.8 ppt), Italy and Slovakia (-0.7 ppts in both cases). At-risk-of poverty rate calculated using an anchored poverty threshold (adjusted for inflation) decreases in all countries but Belgium and Luxembourg.

The structure of the paper is the following: in Section 2 the nowcasting methodology is explained. Section 3 presents and discusses the predictions of the changes in

[3] The United Kingdom is not included because EUROMOD input data is based on Family Resources Survey (FRS). While EU-SILC is a subset of the FRS, the standard nowcasting procedures need to be modified to work on a different input data.

AROP indicators. Section 4 splits the countries into two groups based on their performance. For the first group, which comprises the countries with stable result, we discuss the main drivers behind the changes in AROP rates. For the second group, which consists of countries with problematic results, we reflect on the possible sources of divergence between the nowcasted estimates and the actual EU-SILC indicators for the period in which both are available. Section 5 concludes by summarising the most important findings and policy implications of this research.

2. Methodology

The nowcasting methodology presented in this paper is based on microsimulation techniques used in combination with the latest macro-level statistics. It aims at developing a generic approach that can be applied to all EU countries in a straightforward, flexible and transparent way. By doing so, it ensures the comparability and consistency of results both across countries and through time.

In this work the microsimulation model EUROMOD is used to simulate changes in the income distribution within the period of analysis. Income elements simulated by the model include universal and targeted cash benefits, social insurance contributions and personal direct taxes. Income elements that cannot be simulated mostly concern benefits for which entitlement is based on previous contribution history (e.g. pensions) or unobserved characteristics (e.g. disability benefits). These are read from the survey-based input data and updated according to statutory rules (such as indexation rules) or changes in their average levels over time. Both contributory and non-contributory unemployment benefits are simulated in the model; severance payments are not. Detailed information on EUROMOD and its applications can be found in Sutherland & Figari (2013).

Changes in employment are modelled by explicitly simulating transitions between labour market states (Figari et al., 2011; Fernandez Salgado et al., 2013; Avram et al., 2011). The weighted total number of observations that are selected to go through employment transitions corresponds to the relative net yearly change in employment rates by age group and gender (a total of 6 strata)[4] as shown in the Labour Force Survey (LFS) statistics. Macro-level LFS statistics are used as they are the most up-to-date source of information on employment in the EU. Changes from short-term to long-term unemployment are modelled based on a similar selection procedure, i.e. by using LFS figures on long-term unemployment (with

[4] Eurostat database: code "lfsa_ergaed" and "lfsq_ergaed", employment rates by sex and age (%), annual and quarterly (last accessed on November 30, 2015). At the moment of writing the annual data on 2016 is not available. We use the average of the latest 4 quarters (i.e. 2015Q4, 2016Q1, 2016Q2, and 2016Q3) as a proxy.

unemployment duration more than one year)[5] as an external source of information. This transition is crucial due to its implications for eligibility and receipt of unemployment benefits. Transitions to and from inactivity are modelled implicitly through restricting eligibility for unemployment benefits, according to the country rules.

Observations to go through employment transitions are selected based on their employment probability estimated with a logit model for working age (16-64) individuals using the EUROMOD input data. In order to account for gender differences in the labour market situation, the model is estimated separately for men and women. Students, working-age individuals with permanent disability or in retirement and mothers with children aged below 2 are excluded from the estimation, unless they report employment income in the underlying data. Explanatory variables include age, marital status, education level, country of birth, employment status of partner, unemployment spells of other household members, household size, number of children and their age, home ownership, region of residence and urban (or rural) location. Observations are ranked by their probability and selected for transition until the targeted gender and age-specific employment rate (assed earlier using LFS data) is reached. The specification of the logit model used and the estimated coefficients are reported in the Appendix (Tables A1-A3).

Labour market characteristics and sources of income are adjusted for those observations that are subject to transitions. In particular, employment and self-employment income is set to zero for individuals moving out of employment. For individuals moving into employment, earnings are set equal to the mean among those already employed within the same age-gender group.

Unemployment benefits are simulated for those moving out of employment in case they are eligible for such benefits according to the country rules. If the rules require assessment of earnings and number of months in work for several years preceding unemployment, we assume that these remain unchanged throughout the assessment period and equal to the values observed in the income reference period. For those moving into long-term unemployment the eligibility is adjusted assuming that the duration of unemployment spell is more than one year. In some countries long-term unemployed are not eligible to any unemployment benefits (e.g. Latvia); in other countries they are not eligible for unemployment insurance but still qualify for unemployment assistance (e.g. Greece); in countries with fairly long duration of

5 Eurostat database: code “lfsa_upgan” and “lfsq_upgal”, long-term unemployment (12 months or more) as a percentage of the total unemployment, by sex and age (%), annual and quarterly (last accessed on November 30, 2015). At the moment of writing the annual data on 2016 is not available. We use the average of the latest 4 quarters (i.e. 2015Q4, 2016Q1, 2016Q2, and 2016Q3) as a proxy.

unemployment insurance (e.g. Finland) we assume that long-term unemployed continue to receive unemployment insurance.

After modelling labour market transitions, the next step is to update non-simulated income beyond the income data reference period and to simulate tax and benefit policies for each year from the data income year (i.e. 2011, 2013 or 2014) to the target year (i.e. 2016) using EUROMOD.

Updating incomes and non-simulated benefits is carried out in EUROMOD using factors based on available administrative or survey statistics. Specific updating factors are derived for each income source, reflecting statutory rules (such as indexation rules for pensions) or the change in the average amount per recipient between the income data reference period and the target year. The latter is preferred for the nowcasting exercise, especially in the case of pensions. The evolution of average pensions can capture important changes in the population of pensioners (e.g. an inflow of newly retired pensioner with higher average pensions). In order to capture differential growth rates in employment income, updating factors are disaggregated by economic activity or by economic sector if such information is available.

After updating market income and other non-simulated income sources, EUROMOD simulates (direct) tax and (cash) benefit policies for each year from the base year up to 2016. All simulations are carried out on the basis of the tax-benefit rules in place on the 30th June of the given policy year. The exceptions to this rule are Estonia (2013), Greece (2011, 2013-2015), the Netherlands (2015), and Portugal (2012), where within-year policy changes were taken into account to better match the annual income observed in the EU-SILC data.

In order to enhance the credibility of baseline estimates, an effort has been made to address issues such as tax evasion (in Bulgaria, Greece, Italy and Romania) and benefit non take-up (in Belgium, Estonia, Ireland, Greece, France, Latvia, Portugal, Romania, and Finland). Taking into account these factors leads to improved baseline results and hence, the starting point for the nowcasting estimates. However, such adjustments are not possible to implement in all countries due to data limitations.[6]

For Bulgaria tax evasion adjustments are based on a comparison between net and gross employment incomes. An individual is assumed to be involved in the shadow economy if her (positive) net and gross employment incomes are equal. For Greece tax evasion adjustments have been made on the basis of external estimates for the extent of average income underreporting by income source (earnings, self-employment income from farming and non-farm business). For Italy self-

[6] Detailed information on the scope of simulations, updating factors, non-take-up and tax evasion adjustments is provided in the EUROMOD Country Reports (see https://www.euromod.ac.uk/using-euromod/country-reports).

employment income has been calibrated in order to take into account tax evasion behaviour. For Romania, adjustments for tax compliance (social insurance contributions, health insurance and income tax) are implemented for self-employed in agriculture living in rural areas and with a self-employment income below the average wage.

For Estonia non take-up is simulated for social assistance on the assumption that small entitlements are not claimed. For Belgium and France, non-take up is randomly assigned to attain the same aggregate take-up rates as reported by external sources for the main social assistance benefits; in the case of Greece the same is done for the unemployment assistance benefit for older workers. For Ireland non-take-up is simulated for the family income supplement, applying external estimates on the caseload. In Latvia non-take-up of paternity benefit is taken into account (but it was not possible to do the same for social assistance or housing benefits). In Portugal, non-take-up adjustments are implemented for the social solidarity supplement for the elderly. In Romania similar adjustments are made for the minimum guaranteed income. Finally, in Finland it is assumed that self-employed and adult children living together with their parents do not apply for social assistance.

The last methodological step involves an attempt to account for differences between EUROMOD and EU-SILC estimates of household income in the base year. The main reasons for these discrepancies are related to the precision of simulations when information in the EU-SILC data is limited, issues of benefit non-take-up, under-reporting of income components collected via surveys, tax evasion and small differences in income concepts and definitions.[7]

In order to account for these differences, a calibration factor is calculated for each household. The factor is equal to the absolute difference between the value of equivalised household disposable income in the underlying EU-SILC data and the EUROMOD estimate for the same year and income concept. For consistency reasons, the same household specific factor is applied to all later policy years. This is based on the assumption that the discrepancy between EUROMOD and EU-SILC estimates remains stable over time.

3. The nowcast

This section provides the main nowcast results. We nowcast AROP rates up to 2016 for twenty-seven countries, attempting to predict what EU-SILC 2017 will show once it becomes available. Thus, we are testing the nowcasting methodology for predicting income-based indicators two years ahead: the latest available Eurostat

7 For more detailed information on these issues see Figari et al. (2012) and Jara & Leventi (2014).

indicators at the moment of writing are based on EU-SILC 2015 data (referring to 2014 incomes).[8] The nowcast results are based on EU-SILC 2012 data for 11 countries, EU-SILC 2014 data for 15 countries, and EU-SILC 2015 for 1 country. The choice of data refers to the latest available input data in EUROMOD.[9]

Table 1 shows the nowcasted changes in median equivalised household disposable income and AROP rates between income years 2014 and 2016. The reason for focusing on changes in indicators rather than their absolute values is mainly due to sampling and other errors that may lead to wide confidence intervals around point estimates of the AROP indicators in EU-SILC (see Goedemé, 2010; Goedemé, 2013). Hence, the nowcasts of direction and scale of change are likely to be more reliable than the point estimates for each particular year. The nowcast results use one dataset (i.e. paired samples) to calculate the microsimulation results across all years, which lead to a reduction in the standard errors due to covariance in the data (Goedemé et al., 2013). The statistical significance of changes in the value of indicators between 2014 and 2016, taking into account the covariance in the data, is marked in the tables. The table also reports initial levels for 2014 incomes based on EU-SILC 2015 retrieved from the Eurostat database.

The results show a significant increase in the median equivalised household disposable incomes in nominal terms from 2014 to 2016 in twenty-five out of twenty-seven countries. The exceptions are Cyprus, where the median income decreased (-1.3%), and Luxembourg, with no significant change in the median income level. In the Baltic States, nominal median incomes are predicted to grow by a staggering 18.1% in Estonia, 14.0% in Latvia and 13.9% in Lithuania. This growth is driven by a pronounced wage increase (around 11-12%) accompanied by growth in employment (by 1-2 ppts). Growth in median incomes is also predicted to be high in Bulgaria (12.8%) and Poland (10.2%), where the changes are also driven by an increase in wages and employment. The highest growth is expected in Romania (18.4%) where it is mainly driven by wage growth. Median equivalised household disposable incomes are predicted to increase by 5-7% in the Czech Republic, Ireland, Spain, Hungary, Malta, Austria, Portugal, Slovakia and Sweden. An increase below 5% is estimated for Belgium, Denmark, Germany, Greece, France, Croatia, Italy, the Netherlands, Slovenia and Finland.

Inflation is expected to be quite low in the majority of the countries in 2014-2016. So the differences between expected nominal and real changes in median household

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[8] The only exception is Hungary for which the latest indicators are already based on SILC 2016 (2015 incomes).

[9] EU-SILC 2012 data is used for Belgium, the Czech Republic, Denmark, Germany, Estonia, Ireland, France, Luxembourg, Hungary, the Netherlands and Sweden; EU-SILC 2014 data is used for Bulgaria, Greece, Spain, Croatia, Italy, Cyprus, Lithuania, Malta, Austria, Poland, Portugal, Romania, Slovenia, Slovakia and Finland; EU-SILC 2015 is used for Latvia.

incomes are not large. In fact, in ten countries out of twenty-seven deflation is expected.[10] In Cyprus, Bulgaria, Romania, Croatia, Greece, Spain, and Poland the prices are predicted to fall by 1% or more. In Cyprus the fall in prices is the highest (-2.7%), and it is larger than the expected fall in the median (-1.3%). Thus, in real terms, the median income in Cyprus is expected to increase slightly. Inflation (of 1% or more) is expected in Belgium, Malta, Austria, Sweden, and Portugal. As a result, in the latter four countries the real changes in the median income are somewhat lower than the nominal changes; and in Belgium the median real income is expected to decrease slightly. Changes in real incomes are shown in Appendix (Table A4).

Changes in the total AROP rate are relatively small and not statistically significant in seventeen of the twenty-seven countries. For the remaining ten, the country where relative poverty is predicted to increase the most is Malta with +1.1 ppts from 2014 to 2016. This increase is mainly related to changes in the labour market. A smaller but statistically significant poverty increase is also predicted for Belgium, the Netherlands, Austria and Finland: between +0.4 and +0.8 ppts. These are countries with a comparably low at-risk-of-poverty-rate. In Austria, for example, this can be explained by the effects of the tax reform 2015/2016. Although the reform has led to a tax relief across the income distribution, it had a greater impact on higher income groups. Thus, while overall median income increased, better-off households are expected to have higher increases than low-income households which leads to higher inequality.

The five countries where relative poverty is estimated to decrease the most - and in a statistically significant way - are Poland (-3.6 ppts), followed by Spain (-1.1 ppts), Hungary (-0.8 ppts), Italy and Slovakia (-0.7 ppts in both cases). The substantial drop in poverty in Poland is due to the introduction of new family benefits in 2016. However, nowcasted results may overestimate the impact of the reform, as EUROMOD simulates the new benefit for the full year although it was only rolled out in April 2016. In Spain, decrease in poverty might be related to pronounced increase in employment (more than 3 ppts in 2014-2016). This is also the case in Italy, where also policy changes are likely to have contributed to the significant reduction in the poverty rate. In Slovakia and Hungary the better financial situation in the bottom of the income distribution is associated with improving labour market conditions and wage increase.

The results above describe the changes in the relative poverty (based on the poverty threshold calculated as 60% of the median income). Over the period 2014-2016 the median income changed substantially in some countries. In such cases it is also important to look at the anchored poverty trends (i.e. with the poverty line being

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[10] Inflation forecasts are based on the annual macroeconomic database AMECO: code "ZCPIH", last accessed on January 8, 2017.

fixed in the initial period[11] and adjusted for growth in consumer prices in the following periods). AROP rates calculated using anchored poverty thresholds are predicted to decrease in all countries but Belgium and Luxembourg (see Table A4 in the Appendix). The highest decreases are expected in Poland (-7.1 ppts), Romania (-6.2 ppts), Latvia and Estonia (-5.6 ppts in both cases), and Bulgaria (-4.5 ppts). A decline in anchored AROP of more than 2 ppts is also estimated in Ireland, Croatia, Portugal, Hungary, Slovakia, Lithuania, and Spain.

A comparison of the trends in standard at-risk-of-poverty rate and the anchored poverty rate gives a different perspective on the change in the situation of those with lower incomes. It shows to what extent changes in median income have been in line with the increase in prices (using the Harmonised Index of Consumer Prices). The direction of change in the two indicators might be different if prices and median incomes grow at different pace. Among the countries with significant changes in the standard AROP measure, this is the case for Finland, the Netherlands, Austria and Malta. In all four countries relative poverty risk increases but if the anchored poverty threshold is applied poverty risk seems to decrease.

The relative AROP rates by age group reveal important changes for certain population categories (see Table 1). The nowcasted estimates show that the changes in the poverty risk of elderly population are expected to be substantial in all countries except Denmark, Luxembourg, Slovakia and Sweden. In most countries examined the relative position of the elderly in terms of income is expected to deteriorate. The member states where AROP rates among the elderly are predicted to rise the most are Lithuania (by 8.2 ppts), Estonia (by 6.2 ppts), and Latvia (by 4 ppts). This finding suggests that in countries with high nominal increases in median incomes, pensions have not been able to follow given the existing indexation mechanisms. This is also found to be the case in Bulgaria, Poland and Romania but to a lower extent. In these countries (especially those seriously affected by the crisis) poverty among the elderly exhibited a decreasing trend in the past as, in relative terms, the youth and working-age people were losing more from the economic decline. Once economies started to recover this decreasing trend in the elderly poverty was reversed. In Greece, poverty among the elderly also increases substantially (by 3.7 ppts). This is the only country where pensions have on average decreased from 2014 to 2016.

[11] We anchor the at-risk-of-poverty threshold in the data income year.

Table 1: Nowcast change in median income (%) and AROP rates (ppts) in 2014-2016 and actual indicators for 2014

	Curr enc y	Annual median equivalised househ. disp. income		At-risk-of-poverty rate (AROP)											
				Total		Male		Female		Children (0-17)		Adults (18-64)		Elderly (65+)	
		2014	2014-2016	2014	2014-2016	2014	2014-2016	2014	2014-2016	2014	2014-2016	2014	2014-2016	2014	2014-2016
BE	*EUR*	21,654	1.9***	14.9	0.5**	14.1	0.5**	15.6	0.5**	18.0	0.4*	13.7	0.4*	15.2	1.1***
BG	*BGN*	6,516	12.8***	22.0	-0.4	20.0	-0.8**	23.8	-0.1	25.4	-0.7	18.0	-1.3***	31.7	2.6***
CZ	*CZK*	204,395	5.9***	9.7	0.1	8.5	-0.2	11.0	0.3	14.7	-0.2	9.0	0.0	7.4	0.7***
DK	*DKK*	211,450	1.8***	12.2	-0.3	12.5	-0.4	11.9	-0.2	10.4	-0.3	13.8	-0.4	9.1	0.2
DE	*EUR*	20,668	3.5***	16.7	0.1	15.9	0.0	17.4	0.2	14.6	-0.4*	17.3	-0.3**	16.5	1.8***
EE	*EUR*	7,889	18.1***	21.6	0.1	19.6	-0.5	23.3	0.5	20.0	-1.7***	17.9	-1.0***	35.8	6.2***
IE	*EUR*	21,688	6.8***	16.3	0.5	16.1	0.1	16.4	0.8	17.9	0.4	16.0	0.0	14.2	3.1***
EL	*EUR*	7,520	3.9***	21.4	0.0	21.5	-0.3	21.2	0.3	26.6	-2.6***	22.5	-0.5	13.7	3.7***
ES	*EUR*	13,352	6.9***	22.1	-1.1***	22.5	-1.2***	21.8	-0.9**	29.6	-1.3**	22.8	-1.6***	12.3	1.2***
FR	*EUR*	21,415	3.4***	13.6	0.3	13.2	0.3	13.9	0.2	18.7	0.4	13.4	0.0	8.0	1.1***
HR	*HRK*	41,667	4.5***	20.0	-0.2	19.3	-0.3	20.6	-0.1	20.9	-0.4	17.9	-0.6	26.3	1.6***
IT	*EUR*	15,846	2.3***	19.9	-0.7***	19.0	-0.8***	20.8	-0.5**	26.8	-0.5	19.8	-1.2***	14.7	0.8***
CY	*EUR*	13,793	-1.3**	16.2	0.1	15.3	0.2	17.2	0.0	16.7	0.6	15.9	0.2	17.3	-1.0**
LV	*EUR*	5,828	14.0***	22.5	-0.2	19.7	-0.7*	24.8	0.1	23.2	-1.5**	18.6	-1.2***	34.6	4.0***
LT	*EUR*	5,180	13.9***	22.2	0.8	21.8	-0.4	22.5	1.9***	28.9	0.5	19.5	-1.2**	25.0	8.2***
LU	*EUR*	35,270	-0.7	15.3	-0.1	15.0	0.1	15.7	-0.2	21.5	0.1	14.9	-0.1	7.9	0.0
HU	*HUF*	1,406,56	6.8***	14.9	-0.8***	15.6	-1.1***	14.4	-0.6**	22.7	-1.4**	15.5	-1.1***	4.6	1.0***
M	*EUR*	13,493	5.8***	16.3	1.1**	16.1	0.9*	16.6	1.4***	23.4	0.2	13.1	0.9*	21.0	3.1***
NL	*EUR*	21,292	4.4***	11.6	0.5*	11.8	0.6*	11.5	0.4	14.0	-0.3	12.5	0.3	5.6	2.4***
AT	*EUR*	23,260	5.6***	13.9	0.7***	13.5	0.7***	14.3	0.7***	17.8	1.0*	13.0	0.6***	13.2	0.7***
PL	*PLN*	23,247	10.2***	17.6	-3.6***	18.1	-3.9***	17.2	-3.4***	22.4	-	17.6	-2.3***	12.1	1.7***
PT	*EUR*	8,435	6.3***	19.5	-0.1	18.8	-0.3	20.1	0.2	24.8	-1.0	18.8	-0.7*	17.0	2.9***
RO	*RON*	10,282	18.4***	25.4	-0.7	25.1	-1.0*	25.6	-0.4	38.1	-3.5***	23.3	-0.8*	19.3	3.2***
SI	*EUR*	12,332	2.8***	14.3	-0.2	13.0	-0.2	15.6	-0.3	14.2	-0.7**	13.6	-0.4*	17.2	0.8**
SK	*EUR*	6,930	6.8***	12.3	-0.7*	12.1	-0.8**	12.4	-0.6*	20.1	0.1	11.6	-1.1***	5.6	0.3
FI	*EUR*	23,763	2.2***	12.4	0.4**	12.2	0.3*	12.6	0.4**	10.0	0.8*	12.7	0.2	13.8	0.5**
SE	*SEK*	242,388	5.5***	14.5	-0.2	13.2	-0.2	15.9	-0.2	12.9	-0.5	13.8	-0.2	18.2	0.2

Notes: Estimated changes in 2014-2016 are statistically significant at: * 95% level, ** 99% level, *** 99.9% level. Standard errors around AROP indicators are based on the Taylor linearization using the DASP module for Stata. Only sampling error is taken into account. Household incomes are equivalised using the modified OECD scale. The changes shown are percentage changes in the median and percentage point changes in AROP rates.

Source: Eurostat database: codes "ilc_li02" and "ilc_di03", last accessed on February 12, 2017; EUROMOD Version G4.0+.

The only country where elderly poverty is estimated to decrease is Cyprus (by 1 ppts); in 2014-2016 pensions remained relatively stable in nominal terms whereas other incomes in the economy were falling. Cyprus is the only country where the median and the poverty line are expected to fall. Nevertheless, the experience of other countries shows that elderly poverty decreases only temporarily and that this trend often reverses soon after the economy starts recovering.

Changes in child poverty are expected to be relatively small and not statistically significant in the majority of countries under consideration (see Table 1). In fact, child poverty is only predicted to increase in Belgium, Austria and Finland with 1 ppts or less. In Finland, family benefits decreased from 2014 to 2015 due to a cut of the child benefit. Although the child tax credit was introduced to compensate for the cut, it is only available for working parents. In Belgium, the increase in child poverty is not directly related to cuts in child or family benefits but is likely to be due to the changing employment and income situation of parents. The situation is slightly different in Austria where the tax reform in 2015/2016 has led to less tax burden for the working population. The reform is expected to improve the situation overall but more so for income groups above the poverty threshold which is likely to lead to a higher poverty rate for children. Especially lone mothers who are very often not employed or in part-time employment tend to benefit less.

Poland is the country where child poverty is expected to decrease the most: by staggering 12.8 ppts. This change is mostly driven by the already mentioned roll out of the 500+ family programme, a relatively costly (1.5% of GDP) and overall universal benefit. Child poverty is also expected to decrease substantially in Estonia, Greece, Spain, Latvia, Hungary and Romania (between -1.3 and -3.5 ppts), and to a lesser extent in Germany and Slovenia (less than -1 ppts). In Hungary and Latvia, this change is mostly driven by increasing employment rates and wages in these economies. In addition in Latvia the family benefits became more generous since 2014. In Estonia this positive development is partly related to a substantial increase in the child allowance (in 2015-2016). In Greece, child poverty is predicted to decrease although family benefits have not been increased. This is mostly due to an improved employment situation of parents. The same is likely to be true for Spain. Employment rates have remained rather stable in Romania but employment income increased by staggering 20% which contributes to an improved financial situation of children.

Finally, changes in poverty rates for the working-age population are estimated to be statistically significant for sixteen out of the twenty-seven EU countries (see Table 1). For thirteen out of these sixteen countries the relative position of this population group in terms of income is expected to improve. The biggest poverty reduction is expected in Poland (-2.3 ppts), followed by Bulgaria, Estonia, Spain, Italy, Latvia, Lithuania, Hungary, and Slovakia (around -1 ppts). This development is mostly related to the improving conditions in the labour market of these countries. The country where the AROP rate for the working-age population is estimated to increase is Malta (+0.9 ppts), Austria (+0.6 ppts), and Belgium (+0.4 ppts). No statistically significant changes are predicted for the Czech Republic, Denmark, Ireland, Greece, Croatia, France, Cyprus, Luxembourg, the Netherlands, Finland and Sweden.

4. Discussion

This section focuses on the evolution of AROP rates and compares nowcasted estimates with the official EU-SILC trends. The discussion splits the countries into two groups based on their historical performance. The first group includes countries with a stable and reliable performance: for these countries we highlight the main drivers behind the nowcasted trends. The second group focuses on countries where the nowcasts diverge from the observed actual indicators. For this group we try to explain the causes of the discrepancies.

Across countries, the accuracy of the nowcasts depends on several factors. Observed discrepancies may come from differences in employment composition and the evolution of major income sources (e.g. earnings or pensions) in (EU-SILC based) EUROMOD input data and LFS data which is used to adjust EUROMOD input data to calculate the nowcasted results. While changes in labour market states are carefully taken into account, the wages for new employees are determined in a less sophisticated manner (using average wage within the respective strata). This might lead to further discrepancies especially in countries with fast growing employment. Moreover, changes in the occupational or sector structure are not taken into account. In case such changes are substantial they also may have an impact on the distribution of earnings.[12] No adjustments are made to account for demographic changes or changes in the composition of households. While such changes are usually less critical within a short-term time frame, it might lead to discrepancies in countries with large emigration flows due to shocks (e.g. the recent financial crisis) or population ageing.

Finally, for the purpose of nowcasting EUROMOD results are calibrated to better match the poverty estimates from the EU-SILC. This process attempts to account for differences between EUROMOD and EU-SILC estimates of household income in the data reference year: calibration factors, equal to the absolute difference between the value of equivalised household disposable income in the EU-SILC and EUROMOD data, are calculated for each household. These are then applied to all later years based on the assumption that EUROMOD estimates for disposable income deviate

[12] To some extent this might be the case for Italy in 2016 where the Jobs Act introduced new contract types.

from the equivalent EU-SILC estimates in a fixed way across time. This assumption does not necessarily hold for all households. However, in most cases the predicted *changes* in the AROP rates are not affected by the calibration procedure. For a more detailed discussion on factors influencing the accuracy of nowcasted results see Rastrigina et al. (2015, 2016).

Figures 1a and 1b show the evolution of the nowcasted AROP against the actual EU-SILC indicators. Figure 1a presents the countries where the latest EUROMOD input data is based on SILC 2012. Thus, the nowcasted AROP estimates are for income years 2011-2016 and the actual EU-SILC indicators for income years 2011-2014.[13] Figure 1b shows the same for the countries where the latest available EUROMOD input data is based on SILC 2014. Thus, the nowcasted AROP estimates in Figure 1b are for income years 2013-2016 and the actual indicators are for 2013-2014.[14]

The trend figures show that the nowcasted AROP rates are relatively accurate and fall within the boundaries of the nowcasted confidence intervals for nineteen countries (all except Cyprus, Lithuania, Spain, Estonia, Hungary, Czech Republic, Sweden and Luxembourg). The group of countries with accurate nowcasts has increased since the previous analysis due to the use of more recent input data based on EU-SILC 2014 (compare Figure 1b with Figure A1 in the Appendix and see Rastrigina et al. 2015 for a discussion). The countries for which the results have improved include Bulgaria, Greece, Croatia, Italy, Romania and Slovakia. This shows the importance of using the timeliest input data for the nowcasts as it leaves less room for bias in the predictions. Nevertheless there is a drawback: based on the latest available data it is possible to validate a much shorter period of time (only 2013-2014). Thus, an ex-post validation would be necessary to confirm the reliability of the new estimates for these countries.

Table 2 shows three different nowcast scenarios for countries with stable results to highlight the drivers behind the nowcasted trends. The first scenario shows the nowcasted changes in 2014-2016 for total AROP as presented in Table 1. It takes into account changes in market incomes, labour market characteristics and tax-benefit policy rules. The second scenario keeps labour market characteristics constant (as in the input data) and thus only takes into account changes in market incomes and tax-benefit policy rules. The third scenario compares the situation in 2014 with a hypothetical situation in which the labour market characteristics are

[13] Latvia is also included in Figure 1a. For validation purposes the estimates are produced based on EUROMOD input data derived from SILC 2012. The latest available EUROMOD data for Latvia is SILC 2015. Nowcasts based on this dataset are presented in Table 1. Although the nowcasts based on the latest available data are more precise, such results can't be validated.

[14] For the countries included in Figure 1b it is also possible to produce nowcasts using earlier EUROMOD input data based on SILC 2012. These results are presented in Appendix (Figure A1).

adjusted to resemble 2016 but policy rules and market incomes are fixed constant (as in 2014).

As already discussed in the previous section, significant changes in at-risk-of-poverty are only predicted for ten countries. The factors behind these changes are very different from country to country. The significant decrease in AROP is mainly driven by changes in tax-benefit rules in Poland. The implementation of the family programme is predicted to have led to a sharp decrease in poverty risk from 2015 to 2016. Also in Italy, policy and income changes are estimated to decrease poverty (by -0.6 ppts). The decrease is magnified by changes on the labour market (- 0.2 ppts) due to increasing employment rate since 2014. Increases in employment are also predicted to have contributed to a significant decrease in Slovakia. However, the effect is reduced by tax and benefit changes and changes in market incomes. Also increases in poverty risk are driven by different factors. While the significant increase in Belgium, Malta and Finland is due to labour market changes, it is policy changes and changes in market incomes that are the main drivers of changes in Austria and the Netherlands.

Beside these countries, other countries show no significant changes in total AROP because changes in labour market and policy changes more or less offset each other. For example, this is the case in Bulgaria where the significant increase due to tax-benefit changes and changes in market income is neutralised by labour market changes. The same is true for Germany, France, Croatia and Portugal although the labour market adjustments alone show no significant impact.

The second group of countries where the AROP nowcasts substantially diverge from the actual indicators includes eight countries: Cyprus, Lithuania, Spain, Estonia, Hungary, Czech Republic, Sweden and Luxembourg. In the case of Sweden, Hungary and the Czech Republic, the diverging results seem to be related to changes in the underlying data. Eurostat data are based on several EU-SILC data years while the nowcasted estimates in the three countries are based on EU-SILC 2012 data only. The discrepancies mostly only concern one data point while the estimated nowcasts are in line with Eurostat results in other years. In Hungary and Sweden the discrepancies might result from recent revisions in EU-SILC data that are not part of the EUROMOD input data. In Hungary these revisions affected income distribution in the underlying data. In Sweden monthly activity status over the income reference period was revised. The initial labour market status determines what kind of transition is possible. Thus, errors in the labour market status in the data may lead to errors in the selection of observations for transitions.

In Cyprus the differences are likely to be related to the underreporting of the social assistance benefit in EU-SILC compared to official statistics in 2013, while the simulation in EUROMOD fits very well with the administrative data. In addition, social assistance was turned into the guaranteed minimum income (GMI) welfare benefit. Although there is no official data available yet, it is very likely that this discrepancy prevails also in 2014-2016.

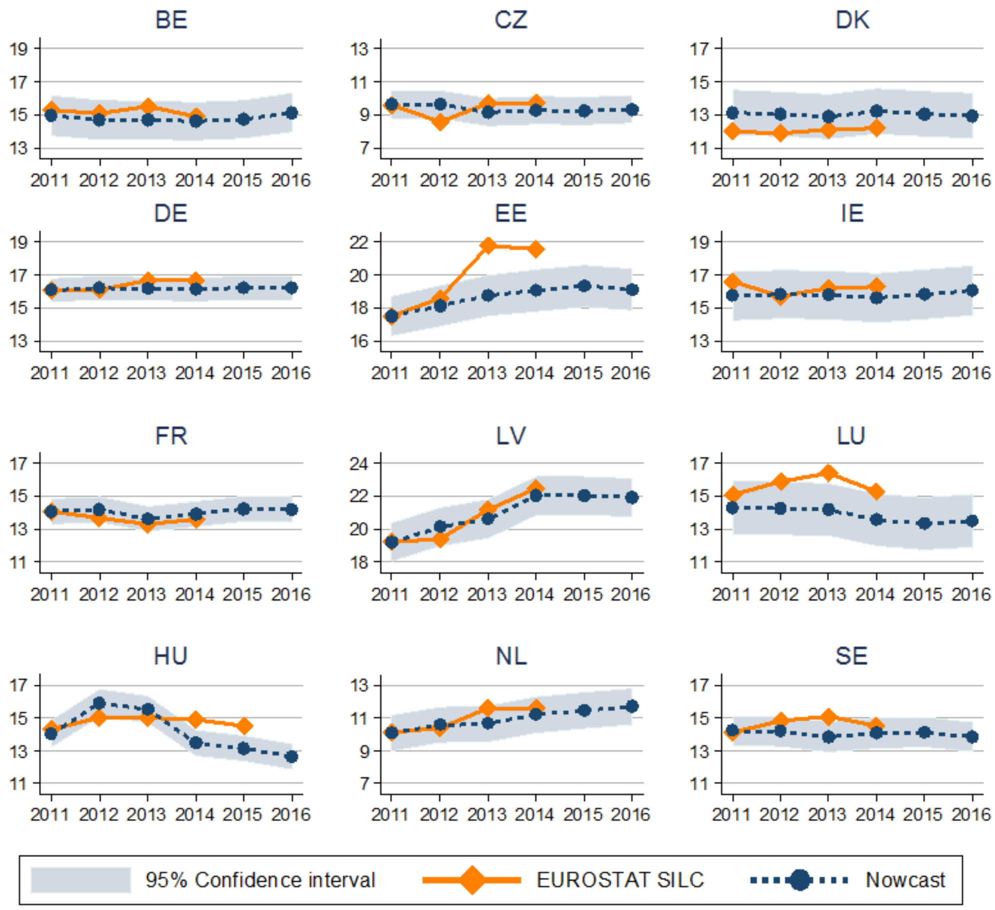
In the case of Spain the observed discrepancies are partly related to the simulation of long-term unemployment. The threshold of 1 year used in the LFS statistics on long-term unemployed does not serve very well in the context of Spain to distinguish recipients of contributory, non-contributory unemployment benefits and those not eligible for any unemployment benefits. Thus, the evolution of the number of recipients of different unemployment benefits in Spain is not well captured.

In Estonia the discrepancies observed in 2013 are primarily caused by the fact that in EU-SILC 2014 missing values for employment income were replaced with register information (which resulted in a structural break in the SILC data). Thus, we cannot reliably check the nowcasted predictions. In this case the nowcasted trend may show how the AROP indicator would have evolved in the absence of the structural break.

In the case of Luxembourg the discrepancies between the nowcasted and the Eurostat level of AROP are caused by the fact that households with at least one international civil servant have been excluded from the EUROMOD input data (645 households), as they have a specific tax-benefit system which is different from the national one. This limitation of EUROMOD is going to be addressed in the next update of the Luxembourg model based on SILC 2015 data.

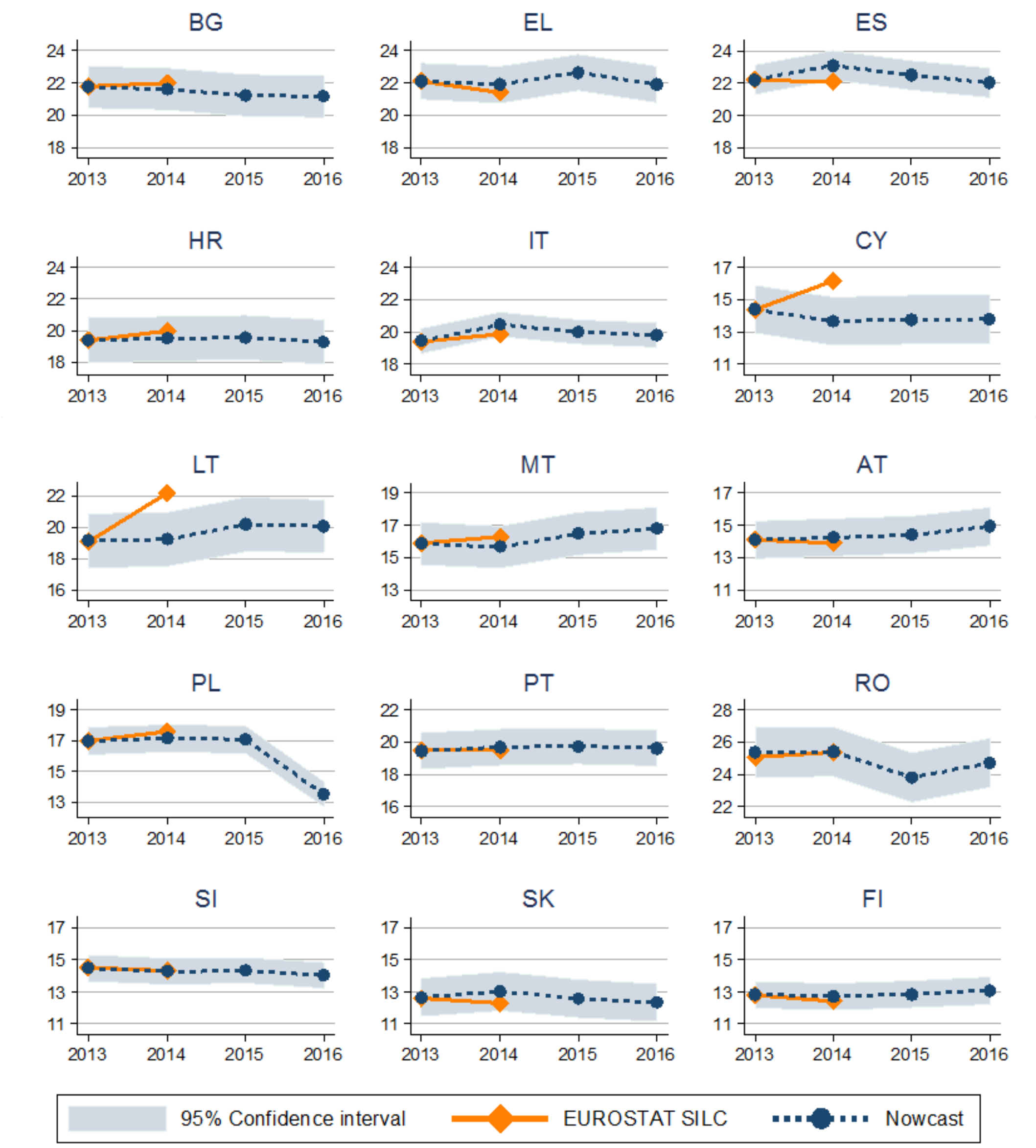
The pronounced increase in poverty in Lithuania between 2013 and 2014 (by 3.1 ppts) is not captured by the nowcasts because the policy measures which are likely to cause this increase can't be fully simulated in EUROMOD. First of all, the increase in poverty might be related to the transfer of responsibility for social assistance to municipalities in 2014. As a result, municipalities became more selective in granting eligibility for social assistance, and the number of recipients reduced (Lazutka, 2014). Second, in this period of time some pensioners were compensated for the pension cuts which occurred during the crisis. However, pensioners with relatively low pensions received no compensation (as their pensions were not cut during the crises). This could have resulted in a temporary increase in inequality between the pensioners and push the more vulnerable ones below the poverty line. Although the direction of change in the number of recipients and aggregate expenditure on both policies is correctly simulated by the model, the differential impact across population groups can't be captured. It also should be taken into account that the standard error around the poverty estimate in the Lithuanian EU-SILC is quite large, hence, the observed increase might overestimate the real change.

Figure 1a: At-risk-of-poverty rates (threshold: 60% of median): EU-SILC and nowcasted estimates (based on 2012 input data)



Notes: Nowcasted estimates are obtained using EUROMOD with employment adjustments and calibration. The vertical scale covers a range of 6 percentage points in all countries, starting from different initial points. The 95% confidence intervals are estimated using the DASP module for Stata. Only sampling error is taken into account. Eurostat SILC data series for Estonia have a structural break in 2013 income (SILC 2014). The discrepancies between the 2011 estimates in Denmark, Ireland and to lesser extent in Hungary are due to revisions in SILC that are not part of the EUROMOD input data. Results for Latvia are produced using SILC 2012 input data for validation purposes.
Source: Eurostat database: code “ilc_li02”, last accessed on February 12, 2017; EUROMOD Version G4.0+.

Figure 1b: At-risk-of-poverty rates (threshold: 60% of median): EU-SILC and nowcasted estimates (based on 2014 input data)



Notes: Nowcasted estimates are obtained using EUROMOD with employment adjustments and calibration. The vertical scale covers a range of 6 percentage points in all countries, starting from different initial points. The 95% confidence intervals are estimated using the DASP module for Stata. Only sampling error is taken into account.
Source: Eurostat database: code "ilc_li02", last accessed on February 12, 2017; EUROMOD Version G4.0+.

Table 2: Nowcast change in total AROP rates (ppts) in three different scenarios, 2014-2016

	Scenario 1	Scenario 2	Scenario 3
	Standard Nowcast	No Labour Market Adjustments	No changes in policy and market incomes
BE	0.5**	0.2	0.3*
BG	-0.4	0.5**	-0.6*
DK	-0.3	0.1	-0.2
DE	0.1	0.3**	0.0
IE	0.5	0.4	-0.4
EL	0.0	0.5	-0.4
FR	0.3	0.4*	0.1
HR	-0.2	0.7***	-0.4
IT	-0.7***	-0.2*	-0.6***
LV	-0.2	0.2	-0.6
MT	1.1**	0.0	1.0**
NL	0.5*	0.5**	0.0
AT	0.7***	0.4**	0.3
PL	-3.6**	-3.6***	0.0
PT	-0.1	0.5**	-0.5
RO	-0.7	-0.7	-0.1
SI	-0.2	0.0	-0.2
SK	-0.7*	0.4**	-1.0***
FI	0.4**	0.1	0.2*

Notes: Estimated changes in 2014-2016 are statistically significant at: * 95% level, ** 99% level, *** 99.9% level. Standard errors around AROP indicators are based on the Taylor linearization using the DASP module for Stata. Only sampling error is taken into account. The changes shown are percentage point changes in AROP rates. Scenario 1: changes in 2014-2016 taking into account changes in market incomes, labour market characteristics and tax-benefit policy rules. Scenario 2: changes in 2014-2016 taking into account only changes in market incomes and tax-benefit policy rules (labour market characteristics are as in the input data). Scenario 3: changes in 2014-2016 taking into account only changes in labour market characteristics (policy rules and market incomes are as in 2014).

5. Summary and Conclusion

The main aim of this paper has been to update previous work on nowcasting the AROP indicator for EU countries. Building on Rastrigina et al. (2016) and Leventi et al. (2017), the analysis was expanded in terms of country coverage (now also including Belgium and Slovenia) and timing of projections (by one or two additional years). The underlying data was updated. AROP rates were nowcasted up to 2016 and the performance of the method was assessed by comparing the predictions with actual EU-SILC indicators for the years for which the latter are available.

The microsimulation model EUROMOD was used to simulate country-specific policy reforms. Changes in the labour market were taken into account by simulating transitions between labour market states. The selection of observations to go through employment transition is based on employment probabilities estimated with a logit model. Based on the EUROMOD input dataset, observations are ranked according to their probability and selected for transition until the age-gender-specific employment rate is reached. A logit model was used for estimating probabilities for working age individuals in the EU-SILC based EUROMOD input data. The total number of individuals that were selected to go through transitions corresponds to the relative net change in employment levels by age group and gender as shown in the LFS macro-level statistics.

The most important findings can be summarised as follows. Median incomes in 2016 are significantly different from their 2014 levels in all countries except for Luxembourg. The highest increases in the median are predicted for Romania, followed by the Baltic States, as well as Poland and Bulgaria. A reduction in the median is only predicted for Cyprus. Changes in relative income poverty are found to be only statistically significant in ten out of the twenty-seven EU member states. The country where the AROP rate for the total population is predicted to increase the most is Malta followed by Belgium, Finland, Austria and the Netherlands. The biggest decreases in the AROP rates are estimated for Poland, followed by Spain, Hungary, Italy and Slovakia. Changes in AROP rates often differ significantly by age-group. Child poverty is estimated to decrease in nine out of twenty-seven countries while it is expected to increase in Austria, Belgium and Finland. Elderly poverty risk, on the other hand, is expected to increase in twenty-two out of twenty-seven countries and only expected to decrease in Cyprus. The anchored poverty risk decreases in all countries but Belgium and Luxembourg.

The comparison of the nowcasted results with the actual EU-SILC indicators has shown that in most cases the two estimates follow the same trends and fall within the boundaries of the nowcasted confidence intervals. The paper splits the countries into two groups. The first group includes countries with a historically stable and reliable performance (nineteen countries out of twenty-seven). The change in poverty rates in these countries can be attributed to different factors. In Poland, the substantial drop seems to be the result of a new family benefit introduced in April 2016. The decrease in income poverty predicted for Slovakia is mostly driven by improved labour market conditions and wage increase. In Italy both increase in employment and policy changes have contributed to the decrease in poverty risk. The significant increases in AROP in Belgium, Malta and Finland are due to labour market changes, while policy changes and changes in market incomes are the main drivers in Austria and the Netherlands.

The second group includes eight countries with problematic nowcasted results. Discrepancies in Cyprus are likely to be driven by the underreporting of the social assistance benefit and guaranteed minimum income in EU-SILC data. In Spain, the definition of long-term unemployed in LFS data is different from definitions used in financial support for long-term unemployed. In Lithuania, the distributional impact of policy changes is not captured very well in EUROMOD. In Luxembourg the discrepancy is due to the fact that households with at least one international civil servant have been excluded from EUROMOD. In Estonia the discrepancy is due to a structural break in the EU-SILC data. Finally, in Hungary, Sweden and the Czech Republic the discrepancies might be related to changes in the underlying data. This analysis shows the manifold reasons for unreliable nowcasting results that need to be further tested and improved. However, the positive trend is that the number of countries with problematic results reduced since the previous study due to the use of more recent input data. This leaves less room for biases in the predictions and highlights the importance of using the latest data for nowcasting changes in median income and AROP rates.

Our nowcasting method is constantly being improved with a view to producing ever more reliable estimates. Further potential developments concern more elaborate estimation of wages for people transitioning from non-employment to employment. Taking into account a wider range of personal and household characteristics in the wage estimation may contribute to better capturing of changes in the income distribution. Another challenge is to take into account short-term changes in economic status. A lot of variation in annual incomes is driven by within year changes of employment status (e.g. precarious work arrangements) which currently are not modelled. Finally, modelling of the financial consequences of long-term unemployment can be improved if country-specific definitions of long-term unemployed are used instead of a common definition. This would be more consistent with the eligibility conditions for benefits within each country and would allow the modelling outcomes of long-term unemployment in a more precise manner.

Nowcasting the main income-related poverty indicators has a potential to facilitate monitoring of the effects of the most recent changes in tax-benefit policies and macro-economic conditions on poverty risk. Given the relevance of these issues to evidence-based policy making and the encouraging results of the comparison of the nowcasting estimates with actual EU-SILC indicators, we believe that this approach constitutes a sound alternative to waiting until official statistics are made available and can provide valuable ex-ante information on potential distributional effects of contemporary economic and policy-related developments.

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Appendix

Table A1: Description of variables used in logit regressions

Variable	Description	Type	Reference category
Dependent			
status	Is employed (according to current self-defined economic status)	dummy	-
Independent			
dag	Age (in the end of income reference period)	continuous	-
dag2	Age squared	continuous	-
married	Married and lives with a partner	dummy	No partner
cohabit	Not married and lives with a partner	dummy	No partner
educ_low	Low level of education (lower secondary or below)	dummy	Medium level of education
educ_high	High level of education (tertiary education)	dummy	Medium level of education
born_eu	Born in a another EU	dummy	Born in the country of residence
born_oth	Born in a country outside EU	dummy	Born in the country of residence
partner_empl	Partner is employed	dummy	No partner
hh_unem	At least one member of the household is unemployed (except own spells)	dummy	No member of household is unemployed
hh_size	Household size	continuous	-
ch_n_age1	Number of children below 3 years old	continuous	-
ch_n_age2	Number of children between 3 year old and compulsory school age	continuous	-
ch_n_age3	Number of children between compulsory school age and 12 years old	continuous	-
ch_n_age4	Number of children between 12 and 24 years old	continuous	-
owner	Accommodation is owned by the households member	dummy	Accommodation is rented (or provided for free)
urban1	Lives in a densely populated area	dummy	Lives in a thinly populated area
urban2	Lives in an intermediate populated area	dummy	Lives in a thinly populated area
reg_*	Regions (NUTS 2 digits)	dummy	First region

Note: The sample includes working age population individuals (aged 16-64). Students, retired, disabled as well as mothers with children below 2 years old are excluded (unless they have positive income).

Table A2: Logit regression coefficients: men

	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY
dag	0.271**	0.295**	0.376**	0.307**	0.247**	0.166**	0.120**	0.222**	0.204**	0.407**	0.255**	0.288**	0.339**
dag2	-0.003**	-0.004**	-0.005**	-0.004**	-0.003**	-0.002**	-0.001**	-0.003**	-0.003**	-0.005**	-0.003**	-0.003**	-0.004**
married	0.335	0.643**	0.658**	0.156	0.878**	1.087**	0.935**	1.146**	0.936**	0.418**	0.701**	0.855**	0.531**
cohabit	0.441*	0.561**	0.691**	0.179	0.477**	0.718**	0.694**	0.871*	0.656**	0.221	0.598	0.604**	0.516
educ_low	-0.893**	-0.974**	-1.398**	-0.211	-0.315*	-0.664**	-0.480**	-0.225*	-0.488**	-0.452**	-0.960**	-0.608**	-0.343*
educ_high	0.429**	0.516**	0.277	0.428*	0.889**	0.805**	0.248	0.453**	0.436**	0.482**	0.623**	0.184	0.523**
born_eu	0.127	-0.046	-0.495	0.598			0.185	-0.28	0.012	0.804**	-0.483	-0.077	0.363
born_oth	-0.970**	-0.736	-0.899	-0.199	-0.166	-0.471*	-0.474	-0.432**	-0.576**	-0.23	0.003	-0.382**	-0.268
partner_empl	0.927**	0.305*	0.509**	0.910**	0.408**	0.333	0.251	-0.159	0.09	0.731**	0.290*	0.044	-0.009
hh_unem	-0.173	-0.477**	-0.468*	0.049	-1.194**	-0.689**	-0.979**	-0.644**	-0.554**	-0.1	-0.179	-0.596**	-0.395**
hh_size	0.177	-0.085	-0.102	-0.287	0.125	-0.108	-0.085	-0.406**	-0.087	-0.386**	0.102	-0.340**	-0.163
ch_n_age1	0.253	0.338	0.177	0.211	0.067	0.154	0.044	0.142	-0.119	0.298	0.196	0.592**	0.184
ch_n_age2	-0.048	-0.087	-0.092	0.476	-0.116	-0.009	-0.103	0.573**	0.08	-0.018	-0.097	0.007	0.5
ch_n_age3	-0.114	-0.19	-0.06	-0.036	0.051	0.182	-0.014	0.08	-0.071	-0.04	-0.001	0.121	-0.098
ch_n_age4	0.118	-0.059	0.19	0.427*	0.117	-0.122	-0.18	0.036	0.028	0.194*	0.005	0.296**	0.285**
urban1	-0.572	0.208	-0.035	-0.752**	-0.329**	0.374**	0.284*	-0.456**	-0.154	-0.294**	-0.102	0.037	-0.22
urban2	-0.129	0.202	0.021	-0.164	0.052		-0.301*	-0.306*	0.065	-0.382**	-0.048	0.034	-0.24
owner	0.463**	0.099	0.318*	0.389*	0.546**	0.466**	0.638**	0.093	0.212*	0.334**	0.055	0.318**	0.203
N	3,338	3,284	5,153	3,894	7,076	3,591	2,643	4,971	8,465	7,219	3,435	12,177	3,121

Note: * p<0.05; ** p<0.01

Table A2: Logit regression coefficients: men *(continued)*

	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE
dag	0.204**	0.139**	0.458**	0.337**	0.544**	0.565**	0.323**	0.147**	0.210**	0.251**	0.566**	0.339**	0.358**	0.473**
dag2	-0.003**	-0.002**	-0.006**	-0.004**	-0.007**	-0.007**	-0.004**	-0.002**	-0.003**	-0.003**	-0.007**	-0.004**	-0.004**	-0.006**
married	0.841**	1.062**	0.074	0.617**	0.798**	0.802**	0.501*	1.016**	0.952**	0.687**	0.448**	0.456*	0.410**	0.232
cohabit	0.736**		0.287	0.338*	0.63	1.136**	0.608*	0.566*	0.470**	-0.618	0.406**	0.302	0.515**	0.377*
educ_low	-0.578**	-1.019**	-0.352	-1.139**	-0.119	0.143	-0.073	-0.859**	-0.289*	-0.181	-0.365**	-1.255**	-0.450**	-0.499**
educ_high	0.598**	1.114**	0.541*	0.634**	0.593**	0.380*	0.187	0.646**	0.350*	0.31	0.682**	0.804**	0.521**	-0.167
born_eu			-0.224	-0.511		-0.194	-0.469	0.887	0.018	-0.133		0.427	0.041	-0.136
born_oth	-0.139	0.128	-0.597*	0.192	-0.39	-0.863**	-0.649**		0.119		0.429**	0.432	-0.173	-0.506*
partner_empl	0.337*	0.449	0.324	0.639**	0.548**	0.331*	0.557**	0.186	0.313*	0.968**	0.524**	0.811**	0.607**	0.826**
hh_unem	-0.526**	-0.638**	-0.184	-0.491**	-0.021	-0.581*	-0.314	-0.265*	-0.397**	-1.452**	-0.223**	-0.961**	-0.314*	-0.061
hh_size	-0.146	0.077	-0.162	-0.09	-0.036	0.128	-0.09	-0.053	-0.264*	-0.129	0.083	0.04	-0.313**	-0.320*
ch_n_age1	0.152	-0.538	-0.259	0.056	0.72	0.481	0.02	0.127	0.059	0.332	0.287	0.353	0.502**	0.479*
ch_n_age2	0.253	0.355	-0.197	-0.178	-0.061	-0.112	-0.07	0.314	0.286	-0.888**	-0.156	-0.073	0.186	0.119
ch_n_age3	0.011	-0.359	-0.022	-0.251**	-0.452*	-0.176	0.084	0.218	-0.058	-0.176	-0.036	-0.155	0.143	0.154
ch_n_age4	-0.079	0.340*	0.460*	-0.034	-0.358	-0.303	-0.11	0.112	0.118	0.131	-0.017	-0.12	0.250*	-0.036
urban1	0.176	0.347*	0.064	0.113	-0.357		-0.668**	0.125	-0.216*	-0.357		0.041	-0.098	-0.035
urban2			-0.378*	0.183*			-0.187	-0.113	0.061	-0.378*		0.143	-0.115	-0.049
owner	0.241	-0.299	0.989**	0.329*	0.461**	0.592**	0.154	0.470**	0.467**	0.012	0.099	0.131	1.091**	0.692**
N	3,237	2,883	3,839	6,972	3,493	7,382	3,564	8,349	4,094	4,259	8,300	4,192	8,057	4,387

Note: * p<0.05; ** p<0.01

Table A3: Logit regression coefficients: women

	BE	BG	CZ	DK	DE	EE	IE	EL	ES	FR	HR	IT	CY
dag	0.358**	0.368**	0.461**	0.359**	0.267**	0.274**	0.201**	0.263**	0.285**	0.454**	0.381**	0.348**	0.334**
dag2	-0.005**	-0.004**	-0.006**	-0.004**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.005**	-0.005**	-0.004**	-0.004**
married	-0.563**	0.006	0.109	-0.416*	-0.496**	-0.606**	-0.133	-0.473**	-0.409**	-0.381**	-0.379*	-0.946**	-0.578**
cohabit	0.121	-0.277	-0.073	-0.616**	0.027	-0.348	0.096	-0.304	0.278	-0.105	-0.850**	-0.339*	-0.446
educ_low	-0.757**	-1.371**	-1.461**	-0.698**	-0.532**	-0.449*	-0.845**	-0.290**	-0.397**	-0.544**	-1.090**	-0.982**	-0.563**
educ_high	0.670**	0.523**	0.688**	0.661**	0.620**	0.836**	0.649**	0.999**	0.790**	0.485**	1.025**	0.705**	0.455**
born_eu	-0.358*	-1.396	-0.149	0.47			-0.04	0.147	-0.29	0.02	0.213	-0.074	0.008
born_oth	-0.698**	-1.359*	-0.086	-0.262	-0.213	-0.175	-0.409	-0.387*	-0.242*	-0.769**	-0.277	-0.474**	0.128
partner_empl	0.811**	0.266	0.261	1.021**	0.470**	0.544**	0.155	0.275*	0.184*	0.678**	0.222	0.262**	0.233
hh_unem	-0.422*	-0.288*	-0.644**	0.452	-0.484**	-0.406*	-0.279	-0.059	-0.251**	-0.04	-0.053	-0.033	-0.18
hh_size	-0.209	-0.06	-0.052	0.378*	-0.05	-0.298*	-0.448**	-0.185	-0.181*	-0.421**	0.162	-0.395**	-0.135
ch_n_age1	-0.403	-0.625	-3.580**	-0.253	-1.284**	-1.085**	-0.443*	-0.134	-0.085	-0.123	-0.268	-0.283	-0.152
ch_n_age2	-0.398*	-0.195	-0.936**	-0.397	-0.441**	-0.241	-0.487**	0.05	0.052	-0.212	-0.479*	-0.135	-0.098
ch_n_age3	-0.227*	-0.242	-0.640**	-0.185	-0.288**	-0.333*	-0.450**	0.034	-0.147*	-0.170*	-0.171	-0.177**	-0.203*
ch_n_age4	-0.107	-0.151	-0.283**	-0.319	-0.210**	0.055	-0.012	0.05	-0.085	-0.158*	-0.217**	0.02	-0.151*
urban1	0.423	0.392**	0.279*	0.04	-0.148	0.162	0.14	-0.273**	0.035	-0.213*	0.430**	0.054	-0.007
urban2	0.504	0.222	0.18	0.135	0.034		0.057	-0.189	-0.13	-0.078	0.131	0.003	-0.23
owner	0.652**	-0.334*	0.185	0.395**	0.327**	-0.176	0.699**	-0.159	0.064	0.344**	0.261	-0.058	-0.015
N	3,282	3,083	4,585	3,748	7,662	3,418	2,806	5,077	8,593	6,916	3,226	12,317	3,212

Note: * p<0.05; ** p<0.01

Table A3: Logit regression coefficients: women *(continued)*

	LV	LT	LU	HU	MT	NL	AT	PL	PT	RO	SI	SK	FI	SE
dag	0.293**	0.338**	0.355**	0.443**	0.421**	0.487**	0.408**	0.299**	0.244**	0.228**	0.730**	0.381**	0.353**	0.486**
dag2	-0.003**	-0.004**	-0.005**	-0.005**	-0.006**	-0.006**	-0.005**	-0.004**	-0.003**	-0.003**	-0.009**	-0.005**	-0.004**	-0.006**
married	-0.389*	-0.321	-1.078**	-0.06	-0.716**	-0.554**	-0.530**	-0.105	-0.017	-0.852**	-0.064	-0.297	-0.062	-0.177
cohabit	-0.125		0.133	-0.234	0.155	0.314	0.361	-0.513**	-0.277	-1.091**	0.16	-0.452	0.024	0.124
educ_low	-0.441**	-1.054**	-0.203	-1.177**	-1.310**	-0.506**	-0.562**	-0.625**	-0.588**	-0.647**	-0.698**	-1.537**	-0.850**	-0.676**
educ_high	1.125**	0.857**	0.550**	0.869**	1.105**	0.693**	0.402**	1.135**	0.415**	0.922**	0.782**	0.661**	0.380**	0.073
born_eu		0.223	0.104	0.583		-0.589*	-0.510**	1	0.910**	-0.279		0.845	-0.104	-0.371
born_oth	-0.311*	-0.647*	-0.36	0.176	-0.34	-0.678**	-0.315		-0.187		-0.085	1.603	-0.564*	-0.783**
partner_empl	0.167	0.450*	0.384*	0.573**	0.370*	0.487**	0.588**	0.201*	0.296*	0.600**	0.533**	0.789**	0.639**	0.581**
hh_unem	-0.163	-0.513*	-0.115	-0.362**	-0.096	0.442	0.094	-0.259*	-0.256*	-0.965**	-0.108	-0.477**	-0.06	0.021
hh_size	-0.049	0.213	-0.034	-0.106	-0.286**	-0.027	-0.117	0.067	-0.251**	-0.135	-0.173*	-0.331**	-0.071	0.032
ch_n_age1	-0.845**	-0.135	-0.229	-3.199**	-0.351	0.121	-0.913**	-0.991**	0.563*	-0.55	0.111	-2.171**	-1.097**	0.208
ch_n_age2	-0.268	-0.591*	-0.25	-1.095**	-0.344	-0.476**	-0.499**	-0.525**	0	-0.276	0.137	-0.925**	-0.278*	-0.420**
ch_n_age3	-0.157	-0.048	-0.462**	-0.748**	-0.434**	-0.480**	-0.284**	-0.333**	-0.101	-0.288**	-0.081	-0.650**	-0.239*	-0.255
ch_n_age4	-0.182	-0.148	-0.135	-0.259**	-0.390**	-0.387**	-0.179	0.009	-0.074	-0.067	-0.195**	-0.12	-0.242**	-0.288*
urban1		0.656**	0.075	0.141	-0.098		-0.274	0.230**	0.219*	0.295*		0.255	-0.163	-0.223
urban2	0.107		-0.077	0.161*			-0.139	-0.117	0.287**	0.221		0.105	0.065	-0.257
owner	-0.024	0.899**	0.218	0.226	0.025	0.482**	0.198	0.243**	0.278**	0.343	0.286**	0.199	0.486**	0.384**
	3,546	3,059	3,965	7,312	3,476	7,241	3,478	8,142	4,421	4,119	7,490	4,145	7,323	4,188

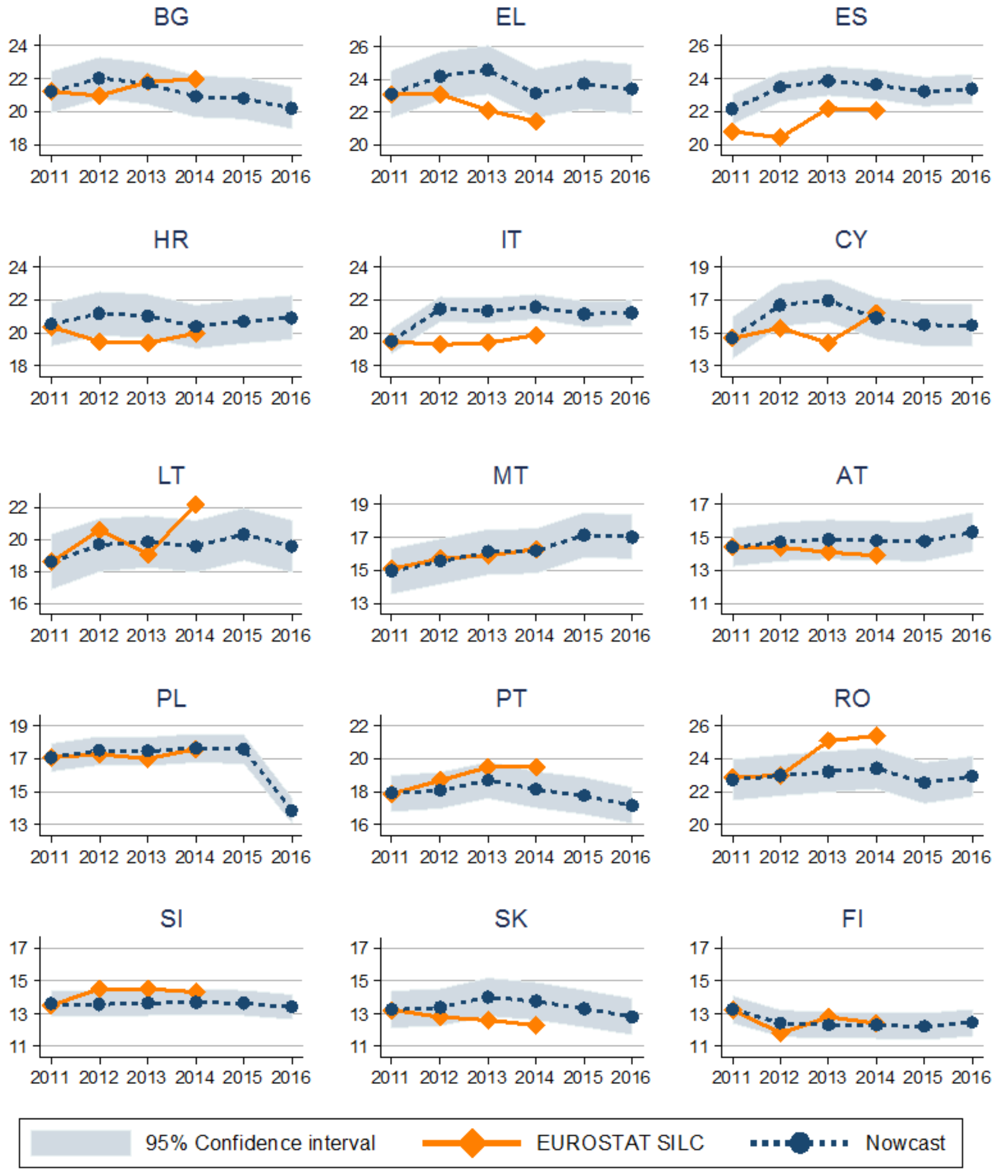
Note: * p<0.05; ** p<0.01

Table A4: Nowcast change in real average employment income (%), real median household income (%) and anchored at-risk-of-poverty rate (ppts), 2014-2016

Country	Harmonized index of consumer prices (HICP)	Real average employment income	Real median household income	Anchored AROP
CY	-2.7	0.3	1.4	-0.5
BG	-2.0	15.7	15.1	-4.5
RO	-1.5	22.1	20.2	-6.2
HR	-1.2	3.7	5.7	-2.1
PL	-1.0	8.5	11.2	-7.1
ES	-1.0	3.7	8.0	-3.9
EL	-1.0	1.4	4.9	-1.5
SK	-0.8	6.9	7.7	-2.6
SI	-0.6	1.8	3.5	-1.8
IE	-0.3	3.5	7.1	-2.1
LT	0.0	11.9	13.9	-3.8
LU	0.0	-0.5	-0.7	0.4
LV	0.1	12.7	13.9	-5.6
IT	0.1	0.7	2.1	-1.7
DK	0.2	2.6	1.6	-0.8
FI	0.2	2.9	2.0	-0.5
NL	0.3	2.0	4.1	-1.2
HU	0.4	8.4	6.4	-2.3
FR	0.4	3.1	3.0	-1.1
DE	0.6	5.6	2.9	-1.1
CZ	0.7	6.6	5.2	-1.7
EE	0.9	10.4	17.0	-5.6
PT	1.2	1.4	5.1	-2.2
SE	1.8	4.5	3.6	-1.1
AT	1.8	0.1	3.8	-0.7
MT	2.2	1.2	3.5	-1.5
BE	2.3	-2.1	-0.4	0.5

Notes: Countries are sorted according to the change in HICP. Nowcasted estimates are obtained using EUROMOD with employment adjustments and calibration. Anchored AROP rates are computed with thresholds fixed in the input data income year and adjusted for HICP in the following years.
Source: HICP – the annual macroeconomic database AMECO: code “ZCPIH”, last accessed on January 8, 2017; EUROMOD Version G4.0+.

Figure A1: At-risk-of-poverty rates (threshold: 60% of median): EU-SILC and nowcasted estimates (based on 2012 input data)



Notes: Nowcasted estimates are obtained using EUROMOD with employment adjustments and calibration. The vertical scale covers a range of 6 percentage points in all countries, starting from different initial points. The 95% confidence intervals are estimated using the DASP module for Stata. Only sampling error is taken into account.
Source: Eurostat database: code "ilc_li02", last accessed on February 12, 2017; EUROMOD Version G4.0+.