Essays on household incomes and public policies

Iva Valentinova Tasseva

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Institute for Social and Economic Research

University of Essex

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Abstract

This thesis studies some of the key factors that influence the distribution of household net incomes in the EU countries. Part of the work analyses the impact of education changes on income inequality. The remaining part of the thesis analyses from different angles the role of tax-benefit policies for household incomes. The thesis consists of four self-contained papers. In the methodology of all papers, I combine a tax-benefit model – EUROMOD – with household micro-data. Chapter 1 is concerned with the impact on income inequality of the substantial increase in the number of university graduates in Great Britain. Chapter 2 studies the impact on the income distribution of automatic stabilisers and discretionary changes to tax-benefit policies in the EU-28. Chapter 3 evaluates ex-post the performance of the main means-tested benefits in Bulgaria in terms of targeting and poverty reduction. Finally, Chapter 4 studies how income poverty is affected by hypothetical changes to the scale of both tax and benefit policies and investigates which are the most cost-effective policies in reducing poverty or limiting its increase in seven diverse EU countries.

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Declarations

Chapter 2 is joint work with Alari Paulus from the University of Essex. I contributed to the development of the research idea and decomposition method. I also contributed to the development of a special Policy Effects Tool in the tax-benefit model EUROMOD, which helped us create the counterfactual scenarios needed for the decomposition analysis and which improved the model capacity to analyse the distributional impact of policy changes. I carried out the empirical work. Finally, I contributed to the writing of each section in the paper. An earlier version of the paper has appeared in the EUROMOD Working Paper Series (EM16/18).

Chapter 3 is based on the version published as Tasseva, I. V. (2016): 'Evaluating the Performance of Means-Tested Benefits in Bulgaria', *Journal of Comparative Economics, 44(4),* 919-935. Earlier versions of the paper have appeared in the series of EUROMOD Working Papers (EM8/12) and ISER Working Papers (No. 2012-18).

Chapter 4 is joint work with Chrysa Leventi and Holly Sutherland from the University of Essex and is based on the version published as Leventi, C., Sutherland, H. and Tasseva, I. V. (2018): 'Improving Poverty Reduction in Europe: What Works Best Where?', *Journal of European Social Policy, 29(1),* 29-43. I contributed to the development of the research plan. I was the main person carrying out the tax-benefit simulations with EUROMOD and the empirical analysis. I contributed to the writing of each section in the paper. Finally, I contributed to the revisions requested for the journal version of the paper. Earlier versions have appeared in the series of EUROMOD Working Papers (EM8/17) and ImPRovE Working Papers (No. 16/16).

"it is wrong to see today's high inequality as the product of forces over which we have no control"

– Tony Atkinson, *"Inequality: What can be done?"*

Introduction

This thesis studies some of the key factors that influence the distribution of household net incomes in the EU countries. Part of the work is concerned with the impact of the recent expansion to higher education on income inequality in Great Britain. The remaining part of the thesis analyses from different angles the role of tax-benefit policies for household incomes in the EU countries. The thesis consists of four self-contained papers which can be split in two groups by the broad research questions they address. Chapter 1 and Chapter 2 study the impact of different factors on the distribution of household net income, using decomposition methods. Chapter 3 and Chapter 4 are both concerned with the effectiveness of tax-benefit policies in reducing poverty. In the methodology of all papers, I combine a tax-benefit model – EUROMOD – with household micro-data.

Decomposing changes in the distribution of income

The distribution of household net income is a complex function that depends on various factors related to tax and benefit policies, gross market incomes and individual and household characteristics. Chapter 1 and Chapter 2 in this thesis identify the contribution to total income changes of some of these factors, by employing decomposition techniques. Despite this similarity, the papers differ from each other substantially in two ways: First, they address different research questions. Chapter 1 is concerned with the impact on income inequality of the substantial increase in the number of university graduates in Great Britain. Chapter 2, on the other hand, studies the impact on the income distribution of automatic stabilisers and discretionary changes to tax-benefit policies in the EU-28. Second, the papers differ from each other methodologically. Chapter 2 refines the method formalised by Bargain and Callan (2010) which, using a tax-benefit model and household micro-data, decomposes changes in the distribution of income into the contribution due to i) discretionary policy changes versus ii) other factors. The paper then includes an extension to the method to decompose the contribution of other factors into the effect due to automatic stabilisers versus changes to market incomes and population characteristics. In comparison, Chapter 1 uses the refined method only; however, using a regression-based approach and re-weighting, Chapter 1 identifies further the contribution of changes in the higher education pay premia, education composition and other population changes.

In more detail, the aim of Chapter 1 is to provide an in-depth account of the link between the expansion of Higher Education (HE) and inequality of household net income in Great Britain for the period 2001-2011. Although many authors have investigated this link in developing countries (see e.g. Bourguignon et al. 2004), we know a lot less about the relationship in developed countries. We find, that all else being equal, education composition changes in Great Britain led to higher living standards mostly through higher wages. As HE expansion benefited households from the middle and top of the distribution more than the bottom, income inequality increased. Despite the increasing share of high-educated workers, the HE wage premium remained broadly unchanged and we find therefore no evidence of a 'compression' effect on inequality.

The second paper, Chapter 2, explores in detail the impact tax-benefit policies had on the distribution of income in various EU countries between 2007 and 2014. Although a large body of literature has studied the impact of tax-benefit policy changes on net incomes, little is known about the link between automatic stabilisers and the income distribution. We fill in this gap in the literature by studying in detail the contribution of automatic stabilisers and discretionary policy changes to changes in the distribution of household net incomes in the EU-28 countries. Our results show that, discretionary policy changes and the automatic stabilisation response of policies overall worked to reduce inequality of net incomes, and so helped offset the inequality-increasing impact of a growing disparity in gross (pre-tax) market incomes. Inequality reduction was achieved mainly through policy changes to benefits and through benefits acting as automatic stabilisers. On the other hand, policy changes to and the automatic stabilisation response of taxes and social insurance contributions raised inequality in some countries and lowered it in others.

The effectiveness of tax-benefit policies in reducing poverty

With its roots in the late nineteenth century, the modern welfare state is now established in all EU countries and one of its most important missions has become poverty reduction. Chapter 3 in this thesis evaluates ex-post the performance of the main means-tested benefits in Bulgaria in terms of targeting and poverty reduction. Chapter 4, on the other hand, studies how income poverty is affected by hypothetical changes to the scale of both tax and benefit policies and investigates which are the most cost-effective policies in reducing poverty or limiting its increase in seven diverse EU countries (one of which is Bulgaria).

In more detail, although there are several means-tested benefits in Bulgaria to protect those at risk of poverty, to date there has been little research on how successful these benefits are in reaching and protecting them. Chapter 3 measures the degree to which benefits are not taken-up by the entitled population (non-take-up) and to which non-entitled are among the benefit recipients (leakage). As the benefits are means-tested – and so ought to target individuals on low incomes by design – we estimate how many of the poor are not being awarded with a benefit (exclusion of the poor) and how many among the recipients are in fact not poor (inclusion of the non-poor). We combine the tax-benefit model EUROMOD with household micro-data: The micro-data tell us which households are receiving the benefits; while EUROMOD allows us to identify the households in the micro-data that are entitled to the benefits. We find that the transfers reach a small proportion of households with incomes below a relative poverty line, they have high non-take-up rates, and large proportions of the recipients are neither poor nor entitled to receive the benefits. Unsurprisingly, although an important income source for poor households, the benefits have a very small impact on reducing the poverty rates. We show that these results are robust to potential underreporting of benefit receipt in the household survey. Through the simulation of reform scenarios we show that there is a large scope for policy improvement.

Finally, Chapter 4, which simulates changes to the scale of policies and looks for the most cost-effective way to reduce poverty, addresses two important limitations of the existing literature. First, while the literature mainly focuses on one type of policy (family benefits), our analysis compares several types of policy instrument within as well as between countries. We consider commonly-applied policy instruments with a direct effect on household income: child benefits, social assistance, income tax lower thresholds and a benchmark case of re-scaling the whole tax-benefit system. Second, while most of the literature concentrates on the poverty-reducing effectiveness of different policy designs, Chapter 4 sheds light on the effectiveness of the scale of given policy designs. Using EUROMOD and household micro-data, we explicitly measure the distributional implications of increasing or reducing the scale of each policy, holding constant its design and national context. Furthermore, to assess the relative cost-effectiveness of the instruments in reducing poverty, we develop an indicator, defined as the ratio of the percentage point change in poverty (headcount or gap) to the net cost to the public budget, expressed as a proportion of GDP. We show that the assessment of the most cost-effective instrument depends on whether the poverty headcount or poverty gap is used as the outcome indicator and on the direction and scale of the change. Nevertheless, our results show that the options that reduce poverty most cost-effectively in most countries are child benefits and social assistance, while reducing the former is a particularly poverty-increasing way of making budgetary cuts.

Tax-benefit microsimulation with behavioural responses

Tax-benefit policies affect household incomes directly through arithmetic changes to tax liabilities and benefit entitlements. But they may also affect household incomes indirectly if individuals make behavioural adjustments in response to their new budget constraints, e.g. in terms of working hours and labour market participation.

Throughout this thesis, it is the direct distributional impact of tax-benefit policies that I am concerned with. The thesis provides a detailed and novel account of these issues using a static microsimulation approach. One limitation of this approach is that it does not allow the estimation of the total effect, i.e. the direct + indirect effects. This distinction becomes irrelevant if there are no indirect effects or if the indirect effects are small in magnitude – in this case, the direct effect is equal to the total effect. Where indirect effects are large, the direct effect alone may still be of interest.

While the indirect effects are not the focus of the thesis and they are not directly estimated, they are however captured in 'other' estimates in Chapter 1 and Chapter 2. The other estimates capture the sum of the indirect effects and other changes that may have occurred over the period of study. The focus of Chapter 3 and Chapter 4 differs slightly: The focus in these chapters is on the simulation of hypothetical policy changes and the estimates are derived assuming there are no behavioural responses. While in practise this assumption may be violated, the estimates for the size of the effects are still reasonable in the absence of large behavioural changes.

Although this thesis does not deal with behavioural reactions to policies, in the rest of this section, I will provide a brief overview of the main approaches of linking microsimulation models with behavioural responses, in particular to labour supply. I will also discuss issues related to incorporating these responses into the analysis. For an overview of tax-benefit microsimulation approaches combined with behavioural models, see e.g. Blundell and MaCurdy (1999), Creedy and Duncan (2002), Bourguignon and Spadaro (2006) and Figari et al. (2015).

Most commonly analysed behavioural responses to tax and benefit policy changes are those related to labour supply choices. The most commonly used labour supply model is the structural discrete choice random utility model (see e.g. van Soest 1995; Aaberge et al. 1995; Blundell et al. 2000). In this setting, individuals face a discrete set of alternatives for labour market participation, e.g. non-participation, working part-time, working full-time or working over-time. The researcher assumes some form for preferences and for each discrete choice, the individual obtains a utility level and disposable income. Individuals face a maximisation problem and choose the labour supply that gives them the highest utility level. The utility function has a random component (usually drawn from an Extreme Value distribution Type I) that affects the optimal choice in terms of utility level. Tax-benefit models, such as EUROMOD, are then used to calculate household disposable income for each household and participation choice. Wages are predicted based on a Heckman-corrected wage equation (either for non-workers only or for both workers and non-workers). The parameters of the utility function are then estimated using the observed labour supply choices. Labour supply elasticities are estimated by simulating the impact on participation of a marginal increase to gross hourly wages. For recent applications using labour supply models linked to EUROMOD, see e.g. Immervoll et al. (2011), Bargain (2012), Bargain et al. (2014), Figari (2015).

Although important to consider for distributional analysis, behavioural models have certain limitations: They can be quite complex and difficult to model. Estimating confidence intervals also becomes more troublesome as modelling individual's behaviour provides additional error to static microsimulation estimates (Pudney and Sutherland, 1996). Behavioural models are based on a set of assumptions about behaviour, model specification and distribution of random terms which can be questionable; and the internal validity of the structural approach can be questioned due to issues concerning omitted variables or selection effects (Bargain and Doorley, 2017). Furthermore, labour supply models are usually estimated on a subsample of the population only – e.g. couples and singles – excluding individuals whose labour supply choices cannot be explained by the factors controlled for in the models (e.g. disabled and students) (Figari et al., 2015).

Labour supply models have been extended to account for macroeconomic feedback effects – e.g. Barrios et al. (2016) link a discrete choice labour supply model with EUROMOD and a dynamic general equilibrium model (QUEST) to analyse the fiscal and distributional impact of tax reforms. Figari and Narazani (2017) link EUROMOD to a joint behavioural model of female labour supply and child care to estimate household responses to changes in child care coverage. Other studies, linking tax-benefit microsimulation with behavioural models, have accounted for e.g. changes to prices and consumption through a general equilibrium model (e.g. see Vandyck and Regemorter (2014) for analysis of the distributional and economic impact of increases to oil excises) or changes to benefit non-take-up behaviour (Pudney et al., 2006).

To conclude, a number of approaches have been developed in the literature to account for behavioural reactions to policies by combining tax-benefit microsimulation with behavioural models. This literature is substantial and differs from the approach taken in this thesis. It would be possible to extend my work in that direction by estimating potential behavioural responses, e.g. to labour supply. Whether such responses have occurred and how large they were is an empirical question and future work on this topic would provide further insights into the issues this thesis is dealing with.

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Chapter 1

The Changing Education Distribution and Income Inequality in Great Britain[1]

Abstract

Over the past years, the number of university graduates increased at an unprecedented rate in Great Britain. We analyse how this higher education (HE) expansion affected inequality in household net incomes in the 2000s. We show that all else being equal, education composition changes led to higher living standards mostly through higher wages. As HE expansion benefited households from the middle and top of the distribution more than the bottom, income inequality increased. Despite the increasing share of high-educated workers, we find no evidence of a 'compression' effect on inequality, as the HE wage premium remained broadly unchanged.

Keywords: higher education expansion; income distribution; decomposition

JEL codes: D31, I24, I26

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1.1 Introduction

Over the past years, there has been an unprecedented increase in the number of university graduates in Great Britain. The share of individuals with at most secondary education fell by 22% between 2001 and 2011; whilst the share of individuals with post-secondary education increased by 30% and the share of higher education (undergraduate and postgraduate) degree holders increased for females by 48% and for males by 40% (Table 1.1). One result of these substantial changes is that the education qualification gap narrowed between males and females; but also between different ethnic groups (Hills et al., 2016a).

These large structural changes in education have important consequences for income inequality. For developing countries in particular, it has been noted that the returns to education are convex and hence, an equally distributed expansion of education among low- and high-skilled can lead to a rise in inequality (Battistón et al., 2014). Bourguignon et al. (2004) refers to this link between education and inequality as the 'paradox of progress'. The literature on the effect of education on income inequality emphasises the 'composition' and 'compression' effects of education expansion (Knight and Sabot, 1983; Gregorio and Lee, 2002; Rehme, 2007; Teulings and van Rens, 2008). With an increase in the relative size of the high-education group, the 'composition' effect initially raises inequality but eventually lowers it as fewer low-educated people remain.[2] The 'compression' effect lowers inequality as the increasing share of educated workers reduces the higher education (HE) wage premium.

The link between recent education trends and household net income inequality in Great Britain is not well understood and the aim of this paper is to provide an in-depth account of this relationship for the period 2001-2011. Brewer et al. (2009) look at summary measures of inequality and find that earnings inequality fell within education groups and the gap in incomes by education groups narrowed in the 1990s and early 2000s.[3] Our paper extends their work by looking at changes along the distribution of income and covers the period of the recent education expansion including the crisis period (2001-11).

In more detail, we estimate the separate effects on the income distribution of changes

[2] Knight and Sabot (1983) show that the impact of the education composition effect on inequality depends on the relative size of the education categories, their relative mean wages and wage variances.

[3] For the 1970s and 1980s, Brewer et al. (2009) find the reverse: an increased gap in earnings and household net incomes within and between education groups.

to the HE wage premia, other changes to wages, and changes to the composition of HE degree holders. We also estimate the effect of changes to tax-benefit policies on incomes. By creating counterfactual distributions of income, the contribution of each of the factors is estimated in isolation from other changes, e.g. we isolate the contribution of the rising number of university graduates to changes in the income distribution, holding constant the graduate pay premium and income tax policy rule. We are also able to examine all these effects across the whole income distribution.

Our approach is to combine the methodologies of Bargain and Callan (2010) and Bourguignon et al. (2008). Using a tax-benefit microsimulation model, we separate out the changes to the tax-benefit policies from the changes to the distribution of gross market incomes and the composition of the population. Using a regression-based approach and re-weighting, we then decompose the latter two to identify the impact on the income distribution of changes in the HE pay premia, education composition and other population changes. The data used come from the Family Resources Survey for Great Britain for 2001/02, 2007/08 and 2011/12.

First, we estimate the distributional impact from changes to the HE wage premium. We find very small income gains and a rise in income inequality in the boom period (2001-07) due to slight increases in the HE wage premium, although these are primarily for white British male workers in the richest 15% of the income distribution. However, during the crisis we find no change in the education earnings differentials by ethnicity and sex groups (consistent with Blundell et al. (2016) and Machin (2011)) and so there is little impact on the distribution of household net incomes. Hence, we find no evidence for a 'compression' effect in the full period 2001-11.

Second, we find evidence for education 'composition' effect. Our results show that, fixing the HE wage premium, HE expansion raised living standards through higher earnings and other market incomes. In the pre-crisis period 2001-07, real mean household income grew by 3.8% due to HE expansion and it rose a further 3.1% during the crisis period 2007-11. However, the income gains due to education made net incomes more unequal as households in the middle and top of the distribution benefited more than those at the bottom.

In a nutshell, between 2001 and 2007, we find that overall income inequality for the middle 95% of the income distribution remained broadly unchanged while it fell between 2007 and 2011. This was despite the upward pressure due to education as well as wage changes, and is due to changes in the tax-benefit system. We show that not only have tax-benefit policies been equalising (consistent with e.g. Sefton et al. (2009), Hills et al. (2014), Hills et al. (2016b)), but also that the drop in inequality in 2007-11 was entirely due to policy changes which benefited mostly the bottom of the distribution.

The rest of the paper is structured as follows: section 2 and 3 describe the methodology, data and the tax-benefit model EUROMOD, section 4 discusses the results and section 5 concludes.

1.2 Methodology

The central question addressed in this paper is, other things being equal, what was the contribution of education composition and education premium changes to changes in the distribution of household net incomes in Great Britain in the 2000s. To answer this, we need to separate the effect of education trends from everything else that could have affected household incomes, such as changes to benefit entitlements and tax liabilities, other compositional changes in the society, or other changes to market incomes. To identify the contribution to total income changes of these different factors, we employ decomposition techniques. The basic idea is that starting from the observed *end-period* income distribution, we can work our way backwards to the observed *start-period* distribution by constructing intermediate counterfactual distributions. By changing different factors one step at a time, the counterfactuals gradually become less like the end-period and more similar and eventually identical to the start-period distribution. A comparison between the different distributions unveils the contribution of each factor to the total change.

First, we decompose the total change in household net incomes into the impact due to changes in population characteristics and market incomes (PCMI) and to changes to tax and benefit policies (TBP). The method follows on the work by Bargain and Callan (2010) who propose a formal framework based on Shorrocks-Shapley decomposition and using a tax-benefit calculator.

Second, we decompose the PCMI effect into the part due to changes in education; the part due to changes to the pay premium by education; and a residual. The method is based on Bourguignon et al. (2008) who build on the work by Juhn et al. (1993) and DiNardo et al. (1996) and propose a regression-based approach and/or re-weighting suitable for decomposing changes in the income distribution. The method builds on the literature generalising the Oaxaca-Blinder decomposition of changes in the mean to changes along the distribution of wages.[4]

In the rest of the section, we first present formally how we decompose the total change in the income distribution into PCMI and TBP effects. Second, we explain how the PCMI effect can be further decomposed to identify the impact of education changes on the income distribution.

1.2.1 Decomposing the total change

Formally, let I be a distribution of household net income (or a functional such as Gini or mean income) and expressed as a function $f(d, r, p, e, x, y, o)$ where d denotes the design of tax-benefit policies (e.g. progressive vs flat tax), r tax-benefit percentage rates (e.g. 20% tax rate), p tax-benefit amounts (e.g. £8,000 personal income tax allowance), e education level (secondary, college, undergraduate, postgraduate), x a vector of other individual/household characteristics, y gross earnings and o other individual/household gross market incomes (e.g. self-employment income). The change in the distribution I between two periods (0 and 1) is

$$\Delta I = f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_0, r_0, p_0, e_0, x_0, y_0, o_0) \tag{1.1}$$

An intermediate, counterfactual distribution is next added (and subtracted) as a function of d, r and p from the end-period but e, x, y and o from the start-period. It yields

[4]See Fortin et al. (2011) for an overview of the literature that decomposes changes in the earnings distribution.

the identity:

$$\Delta I = \underbrace{f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_1, r_1, p_1, e_0, x_0, y_0, o_0)}_{\text{population characteristics and market income effect (nominal)}} \\ + \underbrace{f(d_1, r_1, p_1, e_0, x_0, y_0, o_0) - f(d_0, r_0, p_0, e_0, x_0, y_0, o_0)}_{\text{tax-benefit policy effect (nominal)}} \tag{1.2}$$

The purpose of adding the counterfactual is to answer two questions: i) Given the tax-benefit regime in the end-period, what would have been the impact on I if we would go back to the population and distribution of market incomes from the start-period; and ii) given the population and distribution of market incomes from the start-period, what would have been the impact on I if tax-benefit policies from the end-period were in place? The first term answers i) which identifies the contribution of changes to population characteristics and market incomes (PCMI) (conditional on d, r and p from the end-period) on the total change in I. The second term answers ii) which identifies the contribution of changes to tax-benefit policies (TBP) (conditional on e, x, y and o from the start-period) on the total change in I.

In the counterfactual, tax-benefit amounts from the end-period p_1 are applied on gross market incomes from the start-period y_0 and o_0. To make these comparable (as £1 in period 1 is worth less than £1 in period 0), equation 1.2 is extended to include two counterfactuals in which y_0, o_0 and p_0 are adjusted for inflation by a factor α=Consumer Price Index:

$$\Delta I = \underbrace{f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_1, r_1, p_1, e_0, x_0, \alpha y_0, \alpha o_0)}_{\text{i) population characteristics and market income effect (real)}} \\ + \underbrace{f(d_1, r_1, p_1, e_0, x_0, \alpha y_0, \alpha o_0) - f(d_0, r_0, \alpha p_0, e_0, x_0, \alpha y_0, \alpha o_0)}_{\text{ii) tax-benefit policy effect (real)}} \\ + \underbrace{f(d_0, r_0, \alpha p_0, e_0, x_0, \alpha y_0, \alpha o_0) - f(d_0, r_0, p_0, e_0, x_0, y_0, o_0)}_{\text{iii) nominal effect}} \tag{1.3}$$

For a scale-dependent measure (e.g. mean income), the sum of the first two terms in equation 1.3 gives the *real* change in I and the third term captures the effect of price changes on (start-period) incomes. For a scale-independent measure (e.g. the Gini coefficient) the nominal effect equals 0 as a change in the nominal levels of both tax-benefit policy amounts and market incomes should not affect the relative position of households in the income distribution (Bargain and Callan, 2010). In the results section, we provide estimates of the first two terms only.

The decomposition is path-dependent, e.g. the change in I can be decomposed by conditioning the PCMI effect either on end- or start-period policies. We estimate the effects for all possible combinations and take the average (for details, see Paulus and Tasseva (2018) (Chapter 2 in this thesis)).

1.2.2 Decomposing the changes in PCMI

We decompose the PCMI effect on I to the HE wage premia and separately other changes to wages (hereafter changes to wages), using a regression-based approach. We then separately identify the contribution of changes to the education composition, using re-weighting. Further details are given below.

By constructing new counterfactuals, the first term in equation 1.3 is decomposed as:

$$
\begin{aligned}
\Delta I^{i)} = {} & \underbrace{f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_1},\hat{\delta_1},\hat{\nu_1},\hat{\theta_1},e_1}, o_1)}_{\text{iv) changes to wages}} \\
& \underbrace{f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_1},\hat{\delta_1},\hat{\nu_1},\hat{\theta_1},e_1}, o_1) - f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_1},\hat{\nu_1},\hat{\theta_1},e_1}, o_1)}_{\text{v) changes to returns to HE for white British males}} \\
& \underbrace{f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_1},\hat{\nu_1},\hat{\theta_1},e_1}, o_1) - f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_1},\hat{\theta_1},e_1}, o_1)}_{\text{vi) changes to returns to HE for non-white-British males}} \\
& \underbrace{f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_1},\hat{\theta_1},e_1}, o_1) - f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_1},e_1}, o_1)}_{\text{vii) changes to returns to HE for white British females}} \\
& \underbrace{f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_1},e_1}, o_1) - f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_0},e_1}, o_1)}_{\text{viii) changes to returns to HE for non-white-British females}} \\
& \underbrace{f(d_1, r_1, p_1, e_1, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_0},e_1}, o_1) - f(d_1, r_1, p_1, \hat{e_0}, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_0},\hat{e_0}}, o_1)}_{\text{ix) changes to education composition}} \\
& \underbrace{f(d_1, r_1, p_1, \hat{e_0}, x_1, \hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_0},\hat{e_0}}, o_1) - f(d_1, r_1, p_1, e_0, x_0, \alpha y_0, \alpha o_0)}_{\text{x) residual}}
\end{aligned} \tag{1.4}
$$

In term iv), we estimate the impact on the income distribution of changes to wages, but fixing the HE wage premia and amount of education at their $t = 1$ levels. We construct the counterfactual in iv) as follows: First, the following four models of wages are estimated:

$$\begin{aligned} \ln y_{i(ht)}^{wBm} &= x_{i(ht)}^{wBm}\beta_t + e_{i(ht)}^{wBm}\lambda_t + \epsilon_{i(ht)} \\ \ln y_{i(ht)}^{nwBm} &= x_{i(ht)}^{nwBm}\gamma_t + e_{i(ht)}^{nwBm}\delta_t + \eta_{i(ht)} \\ \ln y_{i(ht)}^{wBf} &= x_{i(ht)}^{wBf}\pi_t + e_{i(ht)}^{wBf}\nu_t + \mu_{i(ht)} \\ \ln y_{i(ht)}^{nwBf} &= x_{i(ht)}^{nwBf}\rho_t + e_{i(ht)}^{nwBf}\theta_t + \upsilon_{i(ht)} \end{aligned} \tag{1.5}$$

where $\ln y_{i(ht)}^{wBm}$, $\ln y_{i(ht)}^{nwBm}$, $\ln y_{i(ht)}^{wBf}$ and $\ln y_{i(ht)}^{nwBf}$ are the log of monthly earnings of individual i in household h in period t for the sample of white British males (wBm), non-white-British males (nwBm), white British females (wBf) and non-white-British females (nwBf), respectively. The e's denote the individual level of education while the x's are a set of other observable individual/household characteristics. The residual terms are denoted by $\epsilon_{i(ht)}$, $\eta_{i(ht)}$, $\mu_{i(ht)}$ and $\upsilon_{i(ht)}$.[5] The returns to individual/household characteristics are denoted with β_t, γ_t, π_t, ρ_t and those to education with λ_t, δ_t, ν_t, θ_t.

Wages are then predicted for the $t = 1$ sample of workers by: a) applying the coefficients $\hat{\beta_0}$, $\hat{\gamma_0}$, $\hat{\pi_0}$ and $\hat{\rho_0}$ from the models estimated on $t = 0$ data; b) applying the returns to higher education (HE) from the models estimated on $t = 1$ data; and c) adjusting the predicted residuals by the ratio of the estimated standard deviation of the residuals in $t = 0$ and $t = 1$. The counterfactual distribution of wages $(\hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_1},\hat{\delta_1},\hat{\nu_1},\hat{\theta_1},e_1})$ represents workers wages in $t = 1$ if they were renumerated according to the returns prevailing in $t = 0$. By adjusting the predicted residuals, changes in the variation of the unobservables are also captured in the counterfactual.

In terms v) to viii), we use the same procedure as above but apply the returns to HE from the models estimated on $t = 0$ data. In this way, we assess the impact of changes to the returns to HE for: v) *white British males* $(\hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_1},\hat{\nu_1},\hat{\theta_1},e_1})$; vi) *non-white-British males* $(\hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_1},\hat{\theta_1},e_1})$; vii) *white British females* $(\hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_1},e_1})$; and viii) *non-white-British females* $(\hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_0},e_1})$. For more details on how we construct

[5] Since the data used in the paper are cross-sectional, we do not have repeated observations for individuals and households which we note with parenthesis $i(ht)$ in equation 1.5.

the wage counterfactuals, see Appendix A.

The term ix) captures the contribution of changes in the amount of education. To construct the counterfactual, we use re-weighting to identify the impact of increased university attainment on I. The re-weighting approach follows on the algorithm by Gomulka (1992). The household survey data weights in $t = 1$ are adjusted to specified control totals for education by age, sex and household type from $t = 0$ while minimising a function of the differences between the old and new weights.[6] By re-weighting and building on the counterfactual from term viii), another wage counterfactual distribution ($\hat{y}^{\hat{\beta_0},\hat{\gamma_0},\hat{\pi_0},\hat{\rho_0},\hat{\lambda_0},\hat{\delta_0},\hat{\nu_0},\hat{\theta_0},\hat{e_0}}$) is constructed in which the education level of the population in $t = 1$ is like of the population in $t = 0$ ($\hat{e_0}$). The counterfactual distribution of education affects not only wages but also other forms of market incomes, as after the re-weighting more/less weight is given to certain household types (classified by education level, age and sex) who may also be more or less likely to receive certain market incomes (e.g. from private pensions and investment income).

Term x) captures the residual, i.e. the impact on the income distribution of all other changes to market incomes and population characteristics not accounted for by the decomposition, e.g. changes in the distribution of self-employment income, migration etc.

In all counterfactuals in terms iv) to x) we apply tax-benefit policies from $t = 1$ using a tax-benefit model. In each scenario the model calculates the counterfactual benefit entitlements and tax liabilities of each individual/household in the end-period, on the basis of their counterfactual wages/education level and end-period other market incomes and characteristics. Household gross incomes minus personal taxes and minus national insurance contributions (NI) gives the distribution of household net incomes in each counterfactual.

Although tax-benefit policies are the same across the counterfactuals, the level of benefit entitlements, personal income taxes and NI differ across scenarios in response to the wage/education changes. This effect is referred to in the literature as the automatic stabilisation effect of tax-benefit policies (Figari et al. 2015, Dolls et al. 2012). We can express the function of household net incomes as the sum of market incomes (conditional

[6]The control totals in the re-weighting are based on the population in the start-period and capture the share of individuals out of the total population by level of education, sex and age (in 5-year bands) and across household type (with/without children and with 1/2+ adults in the household). We make use of the Stata command reweight2 by Browne (2012).

on population characteristics) ($g()$) and benefit entitlements minus personal taxes and NI (conditional on market incomes and population characteristics) ($h()$), $f(d, r, p, e, x, y, o) = g(y, o|e, x) + h(d, r, p|e, x, y, o)$. As household net incomes are decomposable by income source, the change in gross incomes can be separated out from the automatic stabilisation effect of tax-benefit policies.

We provide standard errors for the level and change in income inequality by bootstrapping the population sample 1,000 times. To provide standard errors on the decomposition results for changes in mean incomes we employ the delta method (Taylor approximations). Our estimates account for sample variation but not measurement error.

1.3 Data and the tax-benefit model EUROMOD

We use data from the Family Resources Survey (FRS), which is a purpose built income survey, for 2001/02, 2007/08 and 2011/12. The data are cross-sectional, nationally representative and contain rich information on individual and households characteristics and circumstances. The data series Households Below Average Income (HBAI), which are based on the FRS, are used by different government and non-government bodies, e.g. for analysing income trends by the Department for Work and Pensions (2017) and the Institute for Fiscal Studies (see Hood and Waters (2017)).[7]

To mitigate the risk of measurement error at the bottom of the income distribution (Brewer et al., 2017), we trim the sample by dropping the poorest 4%. Jenkins (2017) shows that HBAI estimates, derived entirely from the FRS data, do not capture changes at the top of the income distribution. Thus, we also drop the richest 1% of the data to reduce measurement error at the top of the distribution. For similar approaches, see Belfield et al. (2017) and Brewer and Wren-Lewis (2015). As a result, our analysis focuses on the middle 95% of the distribution and ignores inequality at the tails. Furthermore, households from Northern Ireland were included in the survey only from 2002/03 onwards and so, we restrict the sample to Great Britain.

To derive household net incomes, we combine information on gross market incomes

[7]The HBAI data contain derived income variables from the FRS and imputations of top earners. However, we use the FRS instead of the derived HBAI variables because we need individual/household-level data on population characteristics and gross incomes.

from the FRS with information on benefit entitlements, income tax liabilities and NI contributions obtained from a tax-benefit microsimulation model. We use the model EUROMOD to calculate benefits, income tax and NI contributions for the actual as well as counterfactual income distributions. This is a standard practice in the decomposition literature which separates changes in the income distribution into direct policy effect (i.e. changes to tax and benefit policies) and population characteristics and market income effect (using EUROMOD, see e.g. Bargain and Callan, 2010 and Bargain, 2012; using IFS TAXBEN, see e.g. Joyce and Sibieta, 2013). EUROMOD contains syntax of functions which determine a) who – e.g. a family with certain characteristics/market incomes – is entitled to receive a certain benefit or liable to pay an income tax/NI and b) the size of the benefit entitlement/personal tax/NI. The syntax reflects the policy rules (design, percentage rates and amounts) on 30th of June in 2001, 2007 and 2011. EUROMOD reads the individual-level FRS data on market incomes and socio-economic characteristics and based on the policy rules it calculates individual/household benefit entitlements, income tax and NI liabilities.

To ensure EUROMOD calculations (given the policy rules and FRS data) reflect the actual income distribution in a given year, the model is regularly tested and validated against official statistics on benefit spending and recipients/tax revenues and payers, and the income distribution. The quality control checks are carried out by a team of researchers at the University of Essex, UK responsible for the maintenance and updating of EUROMOD. The model is publicly available for research purposes and user feedback is fed into the validation process. For more information on the UK model see the Country Report by De Agostini and Sutherland (2016). For a model description and a literature review of research applications with EUROMOD, see Sutherland and Figari (2013) and Figari et al. (2015).

The measure of household net income in this analysis is cash income and is the sum of gross market incomes, national insurance benefits, means-tested benefits, state pensions minus direct income taxes and NI contributions. To account for household composition and economies of scale, we equivalise household net incomes using the modified OECD equivalence scale.

For more detailed information on the data, see Appendix B.

1.4 Results

We begin by documenting the broad distributional changes in the boom (2001-07) and crisis (2007-11) periods, showing that our results using simulated incomes are consistent with the existing evidence. In the second part of the section, we analyse how much of the income changes along the distribution were attributed to changes to population characteristics and market incomes (PCMI) and its components (in particular education), and to changes to the tax-benefit policies (TBP). The final part of the section examines the contribution of changes to PCMI and TBP to changes in income inequality.

1.4.1 Trends in income inequality

We first replicate the broad inequality trends (between 2001 and 2011) that have been documented elsewhere (e.g. Jenkins, 2017 and Belfield et al., 2014), using our simulated incomes derived from EUROMOD model based on FRS data. Table 1.2 shows the change in inequality in 2001-07 and 2007-11, focusing on the middle 95% of the income distribution. We look at five measures of inequality – the Gini coefficient (which is more sensitive to incomes at the centre of the distribution than at the tails), the Atkinson index with aversion parameter equal to 0.5, 1 and 2 (an increase in the parameter value gives more weight to incomes at the bottom tail of the distribution) and the coefficient of variation (which captures the ratio of the income standard deviation to the mean).

Inequality remained broadly unchanged between 2001 and 2007. In the crisis years 2007-11, there was a statistically significant drop in inequality across all measures apart from the coefficient of variation. The Gini fell by 0.006 from 0.274 to 0.268. The Atkinson index with aversion parameter of 0.5, 1 and 2 dropped by 0.002, 0.005 and 0.011 reaching levels of 0.056, 0.106 and 0.189 in 2011, respectively. Only the coefficient of variation continued to remain stable at 0.526 in 2011.

To understand better what is behind the inequality changes, Figure 1.1 shows the real change in mean household net income by ventiles and for the population (all) between 2001 and 2007 and between 2007 and 2011. Mean incomes grew by 8.6% between 2001 and 2007. Incomes rose at all points of the distribution although households from the poorest ventile saw their incomes grow less than the rest of the distribution. The 3rd and 4th ventiles enjoyed the strongest income growth of around 11%. Between 2007 and 2011, the population mean did not change but that masked different trends along the distribution: income growth was pro-poor, except at the top, which explains the drop in inequality. Incomes increased on average by 3.7% for the first 8 ventile groups, with the strongest growth of more than 6% enjoyed by households from the first and second income ventiles. The richest 20th ventile also experienced a small income gain of 1.3%. For the rest of the distribution incomes fell with an average loss of 1.6%.

Appendix C provides evidence that our conclusions about the changes in the income distribution hold, regardless of whether we use simulated incomes (based on EUROMOD and FRS data) or FRS reported incomes. It also discusses the reasons why our results depart from Jenkins (2017), who focuses on the very rich.

1.4.2 Decomposing income changes along the distribution

In this section, we decompose changes in net income at different points of the distribution, for the boom (2001-07) and crisis (2007-11) periods separately. Our aim is to understand what drove income changes at different points of the distribution. We begin by investigating how much of the income changes were attributed to changes to PCMI and its components. We then show the contribution of the TBP effect. We finally compare and contrast the different effects.

To summarise the overall results, we find that changes to PCMI contributed to income gains in the boom period that were pro-rich. During the crisis, they led to changes in net incomes that were U-shaped, with small gains at the bottom and top ventiles and losses along the rest of the distribution. Despite these differences, the largest share of the PCMI effect went to changes to wages and to the education composition which on the whole benefited the upper part of the income distribution more than the bottom in both periods.

Figure 1.2 decomposes the real change in mean household net income by income ventiles between 2001 and 2007. Each subfigure corresponds to a different component of the

PCMI effect (black line), i.e. the contribution to income changes of: changes to wages, excluding the returns to HE; changes to the HE wage premia by sex and ethnicity; compositional changes to education; and a residual. The total change (light grey) and the PCMI effect (grey line) are replicated in each subfigure (the black lines sum up to the grey one). To estimate the impact of changes to wages and the returns to HE, we estimate equation 1.5: the estimated coefficients are broadly as expected and full results are given in Appendix D.

Starting with the changes to PCMI, we find that they account for nearly all of the growth in mean income (all). However, the PCMI effect was regressive in contrast to the total change, with very small gains for the poorest households and the largest gains concentrated in the top 12th-20th ventiles, who saw growth of 9-10%.

The main factors that contributed to the pro-rich income gains due to the PCMI effect were changes to wages (top left subfigure) and compositional changes to education (bottom right subfigure). The changes to wages led to gains in net income that were larger for the second than the first half of the distribution, and the gains due to HE expansion (working through market incomes) were monotonically increasing with income. The increases in net income due to HE expansion, especially at the higher end of the distribution, exceeded those from the changes to wages.

Changes to the HE wage returns for white British men led to tiny income gains for the richest three ventiles. There were no other major income changes driven by changes to the HE wage returns among non-white British men and women. This is broadly consistent with the evidence of constant graduate wage premia (Machin, 2011). Finally, our decomposition results cannot explain all losses at the bottom and gains along the rest of the distribution, captured in the residual.

[Figure 1.2 here]

Figure 1.3 shows results from further decomposing the PCMI components by income source. The sources are: earnings, self-employment income, other market incomes (private pensions, investment income, rent and private transfers between households (received minus paid)) and automatic stabilisers (tax-benefit effect). Taxes and benefits as automatic stabilisers capture the reaction of the (same) tax-benefit policies to changes in market incomes (or changes to population characteristics) (Dolls et al., 2012). Acting as automatic stabilisers, policies in a progressive system such as is the UK are expected to work in the opposite direction to market incomes – when market incomes fall, policies should offset (part of) the loss through lower tax/NI liabilities and increased benefit entitlements and vice versa. Tax-benefit policies would tend to mitigate (part of) the inequality increase in case of more unequally distributed market incomes, but the opposite effect may also be true.

The most striking feature of Figure 1.3 is that changes to wages and HE expansion (i.e. education composition changes) led to increases in earnings that were larger for the middle and top of the income distribution than the bottom; while the automatic stabilisation response of policies was to offset part of these increases. In more detail, we find that changes to wages contributed on average to a rise in earnings of 3.7% but 1.4 percentage points was lost to lower benefit entitlements and/or higher tax/NI liabilities. Earnings fell between the first and sixth ventiles due to wage changes, in contrast to the rest of the distribution. Policies offset the loss by providing net income gains through higher benefits and lower taxes. Self-employment income and other market incomes – mostly private pensions – seemingly changed at different points of the distribution but the effect is entirely due to household re-ranking as a result of the wage changes.

HE expansion led to statistically significant increases in mean earnings (3.9%), self-employment income (0.6%) and other types of market incomes such as private pensions (0.8%) and investment income (0.5%). The gains from earnings, self-employment and investment income were larger for the upper part of the distribution while the gains from private pensions were more equally distributed across households. Tax-benefit policies partly offset the income gains due to HE expansion.

A final notable feature of Figure 1.3 are the income gains from earnings and self-employment income for the bottom ventile groups in the last subfigure showing the residual. This is consistent with Belfield et al. (2017) who document a reduction in the number of males working full-time and an increase in part-time (less than 30 hours per week) employment which is attributed to increased inequality of male earnings. They find an increase in self-employment, in the number of one-earner households and their relative size at the bottom of the distribution. Our results further show that mostly changes to earnings and self-employment income had an income equalising effect, which was partly offset by the regressive automatic stabilisation response of policies.

[Figure 1.3 here]

We now present results from repeating the above analysis for the crisis (2007-11) period. Between 2007 and 2011 and in contrast to the earlier period, the PCMI effect on net incomes led to an average loss of 1.7% (Figure 1.4). The income changes were U-shaped with small gains at the bottom and top ventiles and losses along the rest of the distribution.

As in 2001-07, the main components contributing to the PCMI effect during the crisis were changes to wages and to the education composition. Although changes to wages did not affect average net incomes, they led to small income losses along the entire distribution apart from the 19th and 20th ventiles where incomes rose by 0.7% and substantial 4.8%, respectively. Mean net income rose by 3.1% due to the expansion in education: There were income gains at all parts of the distribution – somewhat larger for the first and last ventiles.

The wage returns to HE (by sex and ethnicity) remained constant in the crisis despite the continuous increase in the number of university graduates. This has also been shown by Blundell et al. (2016) who propose, as an explanation for the constant graduate wage premia, a model in which firms respond to the increased supply of graduates through a decentralisation of the organisation structure. The remaining changes in net income, captured in the residual, show that they were pro-poor resulting in smaller income losses at the bottom than the rest of the distribution.

[Figure 1.4 here]

Decomposing the PCMI components in 2007-11 by income source (Figure 1.5) shows that earnings fell throughout the distribution – apart from the top ventile – due to wage changes but the losses were partly offset by the automatic stabilisation effect of policies. In contrast, the increase in earnings in the top ventile was reduced by the automatic stabilisers.

HE expansion contributed to statistically significant increases in mean earnings (3%) and other market incomes, in particular private pensions (1%). Increases in self-employment income were smaller, (statistically significant at the 10% level) at 0.3%. The tax-benefit system partly reduced the income gains due to changes in the education composition. What is also interesting is that although the impact of HE expansion was not the same across the distribution, policies worked to smooth the effect.

The residual captures market income gains for the second and third ventiles and losses for the rest of the distribution. The fall in market incomes throughout most of the distribution can be largely attributed to the increase in unemployment during the crisis; while the growth in earnings in the second and third ventiles can be explained by further relative increases in the number of one-earner households (compared to no-earner households). In some cases the income loss in gross market incomes exceeded 10%, although the net loss (after taxes and benefits) was less than 6%.

[Figure 1.5 here]

Figure 1.6 now presents the TBP effect (black line). We contrast this to the total change (light grey) and PCMI effect (dark grey line). In both periods, the total change masked opposite trends in the TBP and PCMI effects. Between 2001 and 2007, mean income remained the same due to changes to TBP but across the distribution income changes were pro-poor, contrasting from the regressive PCMI effect. Changes to TBP led to clear income gains for the first half of the distribution, with the largest gains for the poorest households. The income increase enjoyed by households from the poorest ventile was almost entirely due to TBP changes – increased generosity in tax credits and means-tested benefits. The top ventiles, on the other hand, saw their incomes falling by a small but statistically significant share, due to increased tax liabilities and NI contributions. The analysis by Hills et al. (2014) provides an in-depth discussion of the TBP effect in the UK in 2001-07 and 2007-11.

Between 2007 and 2011, the shape of the TBP effect was less progressive compared to the effect in the earlier period and led to gains along the entire distribution (excluding the last ventile), with an average income gain of 1.7%. This result is again different from the U-shaped and mostly negative PCMI effect. The direct effect of the introduction of the top 50% marginal tax rate in 2010/11 can be seen to affect the richest ventile although the behavioural response to the reform – the income forestalling effect – is in fact captured by the PCMI effect. It is noticeable that in both periods the poorest households gained less compared to the following ventile groups due to incomplete benefit take-up. To conclude, policy reactions in the 2000s were working towards increasing the incomes of those at the bottom half of the distribution, thus reducing inequality and offsetting part of the regressive income gains due to changes to PCMI and HE expansion, in particular.

[Figure 1.6 here]

1.4.3 Decomposing inequality changes

After analysing the income changes along the distribution, we turn to decomposing changes in aggregate measures of income inequality in Table 1.3 and Table 1.4. We find that changes to PCMI increased inequality in the 2000s – with the effect being relatively large and positive in the economic growth period (2001-07) and small and not statistically significant in the crisis period (2007-11) (there is a statistically significant change only for the coefficient of variation). As in the previous section, we further decompose the PCMI effects into its subcomponents. Between 2001 and 2007, we find that the inequality increase was mainly driven by changes to the education composition. Between 2007 and 2011, education composition changes as well as changes to wages were the main factors contributing to higher inequality.

In more detail, we find that, the wage changes affected only one out of the 5 inequality measures in 2001-07: they led to a small and statistically significant increase in inequality only for the Atkinson index with an aversion parameter of 2. In 2007-11, the effect of wages was clearly inequality-increasing across all measures.

Looking separately at changes to the wage returns to HE, the aggregate inequality effect (summing rows 4 to 7) was positive but small and masked opposing trends in 2001-07. Namely, the changes to the HE wage returns for white British males and for non-white-British females slightly increased inequality; while changes to the returns for white British female workers were equalising. In the crisis years, the absence of changes to the HE wage premia led to no effect on inequality. Hence, we find no evidence for the 'compression' effect of HE expansion on inequality.

Moving to changes to the education composition, we find that the increase in HE attainment led to higher income inequality in both periods. Our results show that, in the 2001-07 period, HE expansion is also the main component of the PCMI effect that explains the rise in income inequality. In 2007-11, HE expansion continued to widen the gap between rich and poor although to a smaller extent.

The residual did not have any statistically significant impact on inequality in 2001-07. However, between 2007 and 2011, the increase in income inequality, driven by wages and education composition effect, was offset by changes captured in the residual (work patterns and household composition).

Our results for the PCMI effect are consistent with the evidence on wage inequality (Brewer and Wren-Lewis, 2015; Lindley and Machin, 2013). Lindley and Machin (2013) suggest a key explanation for rising wage inequality in the UK is the increased relative demand for educated workers driven by technological change.

Furthermore, the increase in income inequality due to HE expansion is likely to stem from inequality in education attainment. In the 1980s and 1990s, UK HE participation among children from richer families rose faster than among children from poorer backgrounds (Blanden and Machin, 2004). Although education inequality fell in the 2000s, there is limited evidence for a reduction in the inequality at higher levels of education attainment (Blanden and Macmillan, 2014; Crawford, 2012).

Looking at between-group income inequality changes, we find that the income gains due to HE expansion – mostly through higher earnings – for working-age females and non-white-British exceeded the gains for working-age males and white British, respectively. As a result, income inequality in 2000s between sex and ethnic groups fell due to HE expansion, all else being equal. Hence, although education composition changes increased overall inequality, they pushed down between-group inequality among some subgroups (see Appendix E). This finding complements the analysis by Hills et al. (2016a) who show that the HE qualification gap between sex and ethnic groups is closing due to increases in HE attainment but overlook the income changes.

Finally, what seems to have pushed down inequality levels in both periods is tax-benefit policies, especially in the boom period. This result is in line with the literature on the redistributive effect of tax-benefit policy changes which finds that in the majority of EU countries policies have worked towards greater redistribution (see e.g. Hills et al. 2014, De Agostini et al. 2016). Overall, we find that inequality fell in the 2000s through policy changes and most of the effect was achieved in the good years when there was less pressure on the government budget. On the other hand, changes in PCMI worked in the opposite direction, offsetting to a large extent the reduction achieved through policies.

[Table 1.3 here]

[Table 1.4 here]

1.5 Conclusions

The share of individuals with HE in Great Britain increased by 45% between 2001 and 2011. This paper analyses how this recent HE expansion affected the distribution of household net incomes.

We find that between 2001 and 2011 HE expansion led to higher living standards mostly through higher earnings, but the effect was not the same across the income distribution. As households in the middle and the top of the distribution saw their incomes rising faster than households at the bottom, education composition effects raised income inequality (mostly through more unequal earnings distribution). We find no evidence for a wage 'compression' effect. In fact, in the pre-crisis period, income inequality increased as the HE wage premia grew slightly for white British men in the richest 15% of the distribution. In the crisis period, we find that the wage returns to HE remained broadly unchanged with no effect on household incomes.

The inequality-increasing effect from HE expansion is an important policy concern for equality of opportunity if this is the result of HE expansion benefiting disproportionally children from more affluent families. Our data do not allow us to answer directly this question and so, we draw on the related literature: although, as the average level of education attainment increased, education inequality fell in the 2000s (compared to an increase in the 1980s and 1990s), there is limited evidence showing that inequality at higher levels of education attainment has fallen (Blanden and Macmillan, 2014; Crawford, 2012). Furthermore, the positive link between HE expansion and income inequality may have implications for social mobility. International comparisons suggest low levels of intergenerational income mobility in the UK linked to the relatively high level of income inequality, with education attainment as a key driver for this relationship (Corak, 2013; Jerrim and Macmillan, 2015). There is also evidence suggesting that social mobility in the UK is falling (Gregg et al., 2017; Nicoletti and Ermisch, 2007) although the links to changes to income inequality have not been studied so far.

Apart from HE expansion, we find that other forces related to the tax and benefit system had an important impact on the income distribution. We confirm that, in both periods 2001-07 and 2007-11, changes to tax and benefit policies – in particular, the increased generosity of tax credits, higher tax and national insurance rates – worked towards inequality reduction and offset most of the inequality increase caused by HE expansion. Furthermore, the automatic stabilisation response of policies to changes in the underlying distribution of market incomes and population characteristics were also broadly income-equalising.

Despite the reduction in income inequality in the late 2000s and its subsequent stability (Department for Work and Pensions, 2017), planned benefit cuts and earnings growth are projected to raise inequality (Hood and Waters, 2017). With the continuous expansion of HE, further increases in income inequality may also be expected due to the composition effect until eventually inequality peaks and starts to fall. On the other hand, it is likely that the expansion of HE will eventually push down the education wage differential and, with it, income inequality. It remains to be seen how the changing education distribution will play out on income inequality in the future.

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1.6 Tables

Table 1.1:
Education shares (in %)

	2001	2007	2011
Males			
Secondary	62.0	55.2	50.5
College	17.2	18.9	20.4
Undergraduate	10.0	12.8	14.9
Postgraduate	10.8	13.0	14.3
Females			
Secondary	61.5	54.1	49.3
College	20.1	21.6	23.1
Undergraduate	10.7	13.1	15.4
Postgraduate	7.7	11.2	12.3
All			
Secondary	61.7	54.7	49.9
College	18.7	20.3	21.8
Undergraduate	10.4	13.0	15.1
Postgraduate	9.2	12.1	13.2

Notes: Sample includes individuals aged 15-64. *Secondary*=in education/left school aged <=16/missing information. *College*=in education/left school aged >16 and <=18. *Undergraduate*=in education/left school aged >18 and <=21.

Postgraduate=in education/left school aged >21.

Source: Authors' calculations using the Family Resources Survey for 2001/02 (2001), 2007/08 (2007) and 2011/12 (2011).

Table 1.2:
Level of and changes (in % points) to inequality

	Gini	Atkinson (0.5)	Atkinson (1)	Atkinson (2)	CV
observed 2001	.277***	.059***	.113***	.205***	.531***
	(.001)	(.001)	(.001)	(.002)	(.003)
observed 2007	.274***	.058***	.111***	.201***	.529***
	(.002)	(.001)	(.001)	(.002)	(.004)
observed 2011	.268***	.056***	.106***	.189***	.526***
	(.002)	(.001)	(.001)	(.002)	(.005)
total change in 2001-07	-.003	-.001	-.002	-.004	-.002
	(.002)	(.001)	(.002)	(.002)	(.005)
total change in 2007-11	-.006**	-.002**	-.005***	-.011***	-.003
	(.002)	(.001)	(.002)	(.003)	(.006)

Notes: HE=higher education. Significance levels indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 1,000 replications.

Source: Authors' calculations using EUROMOD and the Family Resources Survey.

Table 1.3:
Decomposing inequality changes (in % points) between 2001 and 2007

	Gini	Atkinson (0.5)	Atkinson (1)	Atkinson (2)	CV
total change	-.003	-.001	-.002	-.004	-.002
	(.002)	(.001)	(.002)	(.002)	(.005)
PCMI effect	.010***	.004***	.009***	.016***	.019***
	(.002)	(.001)	(.002)	(.003)	(.005)

iv) changes to wages	.000	.000	.001	.003***	-.004
	(.001)	(.000)	(.001)	(.001)	(.003)
v) changes to returns to HE: wBm	.002***	.001***	.001***	.002***	.005***
	(.000)	(.000)	(.000)	(.000)	(.001)
vi) changes to returns to HE: nwBm	.000	.000	.000	.000	.001
	(.000)	(.000)	(.000)	(.000)	(.001)
vii) changes to returns to HE: wBf	-.001***	-.000***	-.000***	-.001***	-.001***
	(.000)	(.000)	(.000)	(.000)	(.000)
viii) changes to returns to HE: nwBf	.001***	.000***	.001***	.001***	.002***
	(.000)	(.000)	(.000)	(.000)	(.000)
ix) changes to education composition	.007***	.003***	.006***	.010***	.016***
	(.001)	(.000)	(.001)	(.001)	(.002)
x) residual	.001	.000	.001	.001	.001
	(.002)	(.001)	(.001)	(.002)	(.005)
TBP effect	-.013***	-.005***	-.011***	-.020***	-.021***
	(.000)	(.000)	(.000)	(.000)	(.001)

Notes: HE=higher education; wBm=white British males; nwBm=non-white-British males; wBf=white British females; nwBf=non-white-British females; PCMI=population characteristics and market incomes; TBP=tax-benefit policies. Significance levels indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 1,000 replications.

Source: Authors' calculations using EUROMOD and the Family Resources Survey.

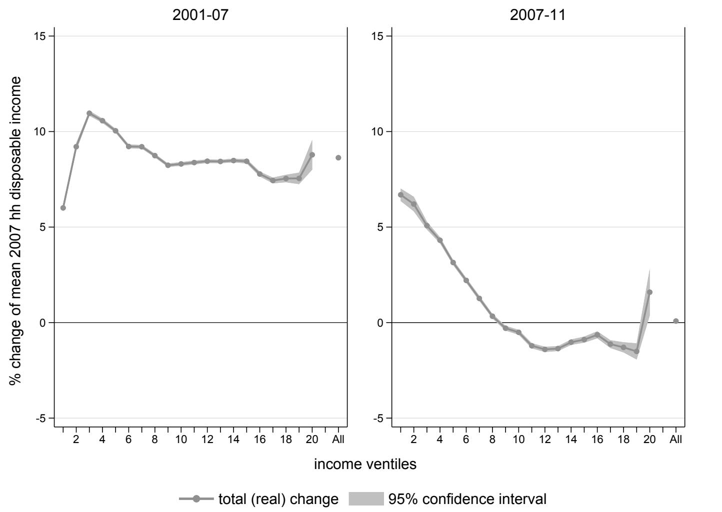
Table 1.4:
Decomposing inequality changes (in % points) between 2007 and 2011

	Gini	Atkinson (0.5)	Atkinson (1)	Atkinson (2)	CV
total change	-.006**	-.002**	-.005***	-.011***	-.003
	(.002)	(.001)	(.002)	(.003)	(.006)
PCMI effect	.001	.001	.001	-.002	.015**
	(.002)	(.001)	(.002)	(.003)	(.006)
iv) changes to wages	.006***	.003***	.004***	.005***	.022***
	(.001)	(.000)	(.001)	(.001)	(.003)
v) changes to returns to HE: wBm	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.001)
vi) changes to returns to HE: nwBm	.000	.000	.000	.000	.000
	(.000)	(.000)	(.000)	(.000)	(.001)
vii) changes to returns to HE: wBf	-.000*	-.000	-.000	-.000*	-.000
	(.000)	(.000)	(.000)	(.000)	(.001)
viii) changes to returns to HE: nwBf	-.000	-.000	-.000	-.000	-.000
	(.000)	(.000)	(.000)	(.000)	(.001)
ix) changes to education composition	.002***	.001***	.001***	.002***	.005***
	(.001)	(.000)	(.000)	(.001)	(.002)
x) residual	-.006***	-.003***	-.005***	-.009***	-.011**
	(.002)	(.001)	(.002)	(.003)	(.005)
TBP effect	-.007***	-.003***	-.006***	-.010***	-.018***
	(.000)	(.000)	(.000)	(.001)	(.002)

Notes and Source: see Table 1.3

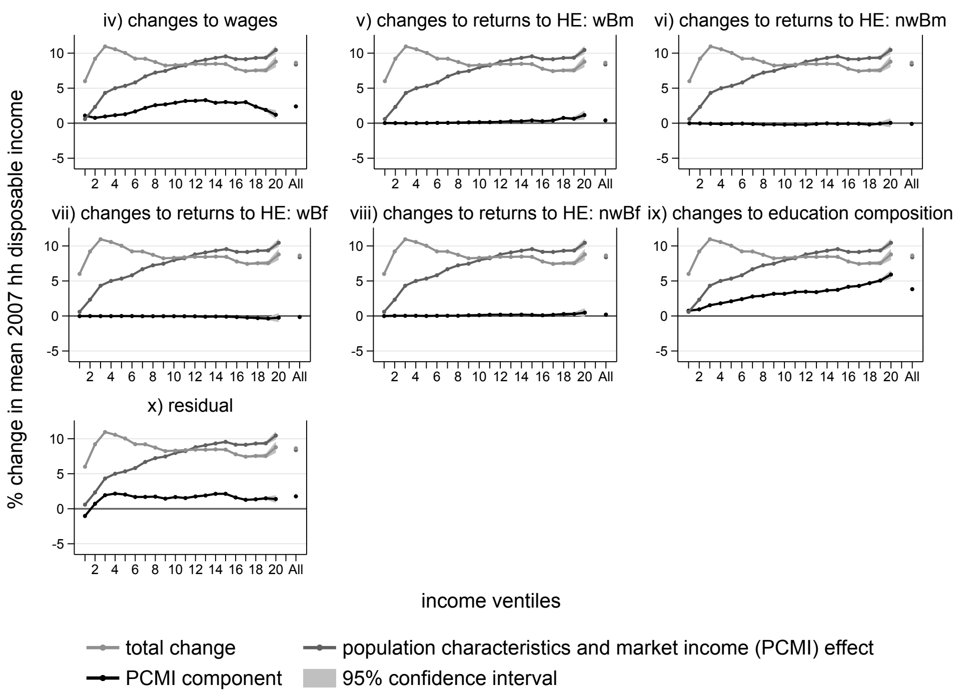
1.7 Figures

Figure 1.1: *Change in mean incomes between 2001 and 2007 and 2007 and 2011*



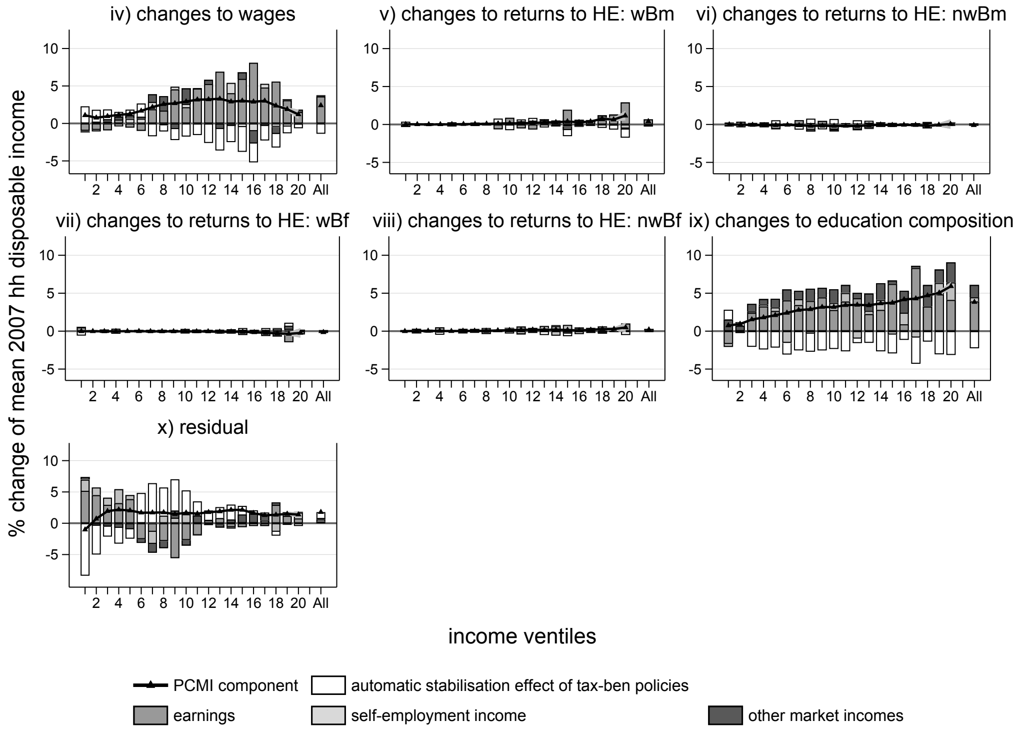
Notes: Confidence intervals are estimated using the delta method (Taylor approximations).
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Figure 1.2: *Decomposing the change in mean incomes between 2001 and 2007*



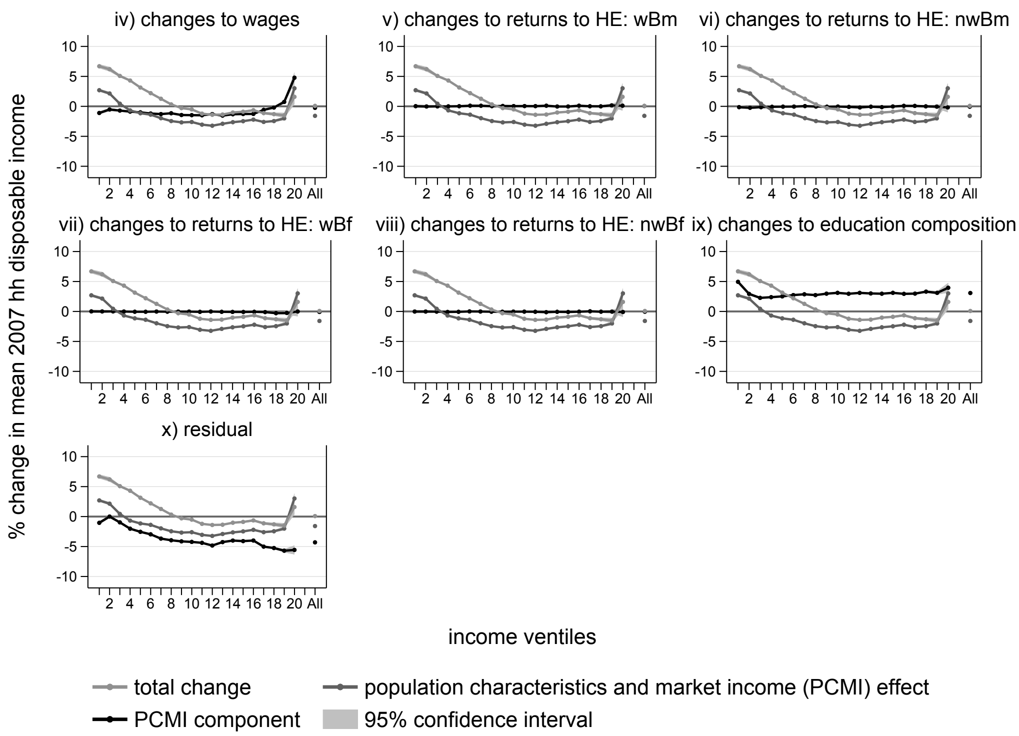
Notes: HE=higher education; wBm=white British males; nwBm=non-white-British males; wBf=white British females; nwBf=non-white-British females. The light and dark grey lines are the same in all subfigures. The black lines add up to the dark grey line. Confidence intervals are estimated using the delta method (Taylor approximations).
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Figure 1.3: *Decomposing the change in mean incomes (by income type) due to changes in PCMI, between 2001 and 2007*



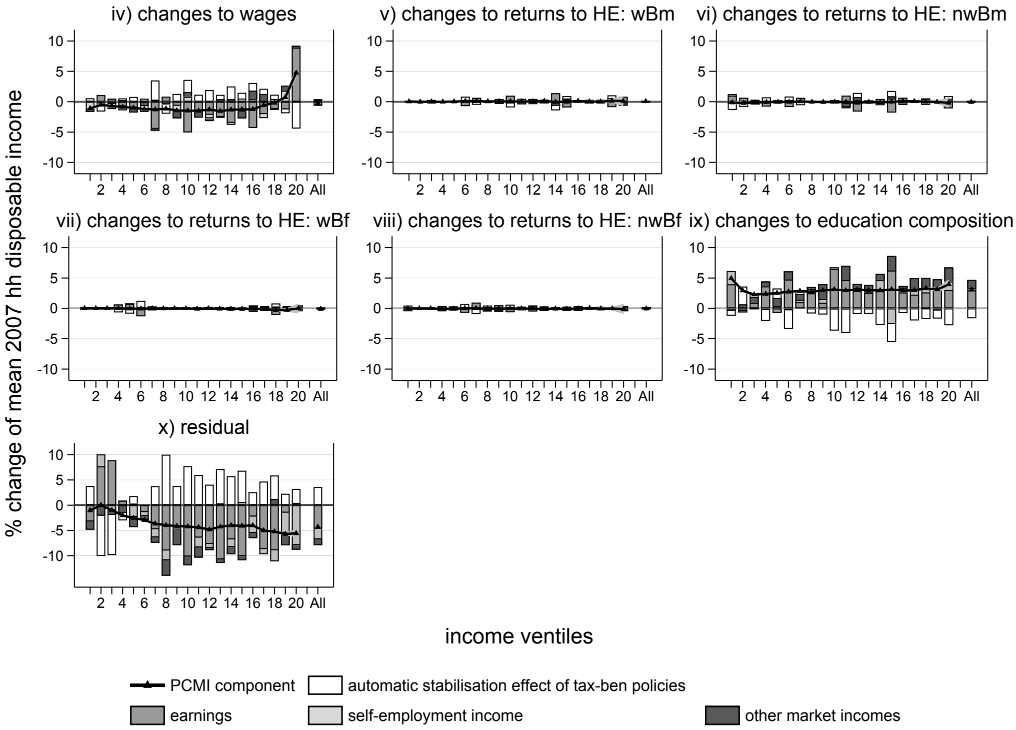
Notes: HE=higher education; wBm=white British males; nwBm=non-white-British males; wBf=white British females; nwBf=non-white-British females. The bars add up to the black line in each subfigure. Confidence intervals are estimated using the delta method (Taylor approximations).
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Figure 1.4: *Decomposing the change in mean incomes between 2007 and 2011*



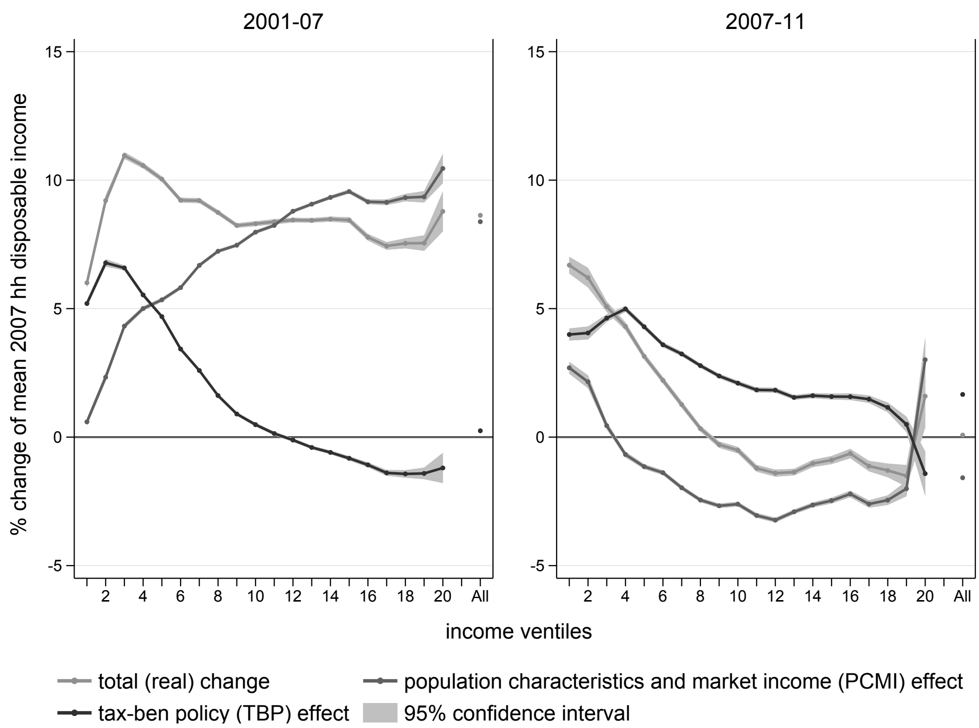
Notes and Source: see Figure 1.2.

Figure 1.5: *Decomposing the change in mean incomes (by income type) due to changes in PCMI between 2007 and 2011*



Notes and Source: see Figure 1.3.

Figure 1.6: *Decomposing the change in mean incomes between 2001 and 2007 and 2007 and 2011*



Notes: The black and dark grey lines add up to the light grey line. Confidence intervals are estimated using the delta method (Taylor approximations).
Source: Author's calculations using EUROMOD and the Family Resources Survey.

1.8 Supplementary materials

1.8.1 Appendix A

In term iv) of equation 1.4, we estimate the impact on the income distribution of changes to wages, but fixing the HE wage premia and amount of education at their $t = 1$ levels. To construct the counterfactual in term iv), wages are hence predicted for the $t = 1$ sample of workers by: a) applying the coefficients $\hat{\beta}_0$, $\hat{\gamma}_0$, $\hat{\pi}_0$ and $\hat{\rho}_0$ from the models estimated on $t = 0$ data; b) applying the returns to higher education (HE) from the models estimated on $t = 1$ data; and c) adjusting the predicted residuals by the ratio of the estimated standard deviation of the residuals in $t = 0$ and $t = 1$:

$$\begin{aligned}
\ln \hat{y}^{wBm}_{i(h)} &= x^{wBm}_{i(h1)}\hat{\beta}_0 + e^{wBm}_{i(h1)}\hat{\lambda}_1 + \hat{\epsilon}_{i(h1)} * \frac{\sigma(\hat{\epsilon}_{i(h0)})}{\sigma(\hat{\epsilon}_{i(h1)})} \\
\ln \hat{y}^{nwBm}_{i(h)} &= x^{nwBm}_{i(h1)}\hat{\gamma}_0 + e^{nwBm}_{i(h1)}\hat{\delta}_1 + \hat{\eta}_{i(h1)} * \frac{\sigma(\hat{\eta}_{i(h0)})}{\sigma(\hat{\eta}_{i(h1)})} \\
\ln \hat{y}^{wBf}_{i(h)} &= x^{wBf}_{i(h1)}\hat{\pi}_0 + e^{wBf}_{i(h1)}\hat{\nu}_1 + \hat{\mu}_{i(h1)} * \frac{\sigma(\hat{\mu}_{i(h0)})}{\sigma(\hat{\mu}_{i(h1)})} \\
\ln \hat{y}^{nwBf}_{i(h)} &= x^{nwBf}_{i(h1)}\hat{\rho}_0 + e^{nwBf}_{i(h1)}\hat{\theta}_1 + \hat{\upsilon}_{i(h1)} * \frac{\sigma(\hat{\upsilon}_{i(h0)})}{\sigma(\hat{\upsilon}_{i(h1)})}
\end{aligned} \tag{1.6}$$

In terms v) to viii) of equation 1.4, we use the same procedure as above but apply the returns to HE from the models estimated on $t = 0$ data. The counterfactual wages are:

$$\begin{aligned}
\ln \hat{y}^{wBm}_{i(h)} &= x^{wBm}_{i(h1)}\hat{\beta}_0 + e^{wBm}_{i(h1)}\hat{\lambda}_0 + \hat{\epsilon}_{i(h1)} * \frac{\sigma(\hat{\epsilon}_{i(h0)})}{\sigma(\hat{\epsilon}_{i(h1)})} \\
\ln \hat{y}^{nwBm}_{i(h)} &= x^{nwBm}_{i(h1)}\hat{\gamma}_0 + e^{nwBm}_{i(h1)}\hat{\delta}_0 + \hat{\eta}_{i(h1)} * \frac{\sigma(\hat{\eta}_{i(h0)})}{\sigma(\hat{\eta}_{i(h1)})} \\
\ln \hat{y}^{wBf}_{i(h)} &= x^{wBf}_{i(h1)}\hat{\pi}_0 + e^{wBf}_{i(h1)}\hat{\nu}_0 + \hat{\mu}_{i(h1)} * \frac{\sigma(\hat{\mu}_{i(h0)})}{\sigma(\hat{\mu}_{i(h1)})} \\
\ln \hat{y}^{nwBf}_{i(h)} &= x^{nwBf}_{i(h1)}\hat{\rho}_0 + e^{nwBf}_{i(h1)}\hat{\theta}_0 + \hat{\upsilon}_{i(h1)} * \frac{\sigma(\hat{\upsilon}_{i(h0)})}{\sigma(\hat{\upsilon}_{i(h1)})}
\end{aligned} \tag{1.7}$$

1.8.2 Appendix B

Education

The FRS has only one education variable (on age completed full-time education, variable 'tea') that is consistent across the three years of data used in the paper.[8] Therefore, this is the variable we use in the paper. The variable has been used by other economists (Brewer and Wren-Lewis, 2015).

Table 1.5 compares the FRS education distribution to the LFS education distribution. The higher education (HE) variable of the paper consists of 2 categories (undergraduate and postgraduate). We combine these two categories to make them comparable to the published LFS statistics. Table 1.5 shows that the FRS and LFS are similar in levels – the share of people with university degree is about the same in 2007 (28.7% in LFS vs 27.9% in FRS) and in 2011 (33.2% in LFS vs 31.7% in FRS); in 2001 the share in LFS is somewhat higher (25.9%) than in FRS (22.1%). As a result, the trends are quite similar for the 2007-11 period (4.5 percentage points (pp) increase in LFS vs 3.8pp in FRS) although less so for the 2001-07 period (2.8pp increase in LFS vs 5.8pp in FRS). This comparison suggests that our results for the impact on the income distribution of the HE expansion may be overestimated for the period 2001-07 since our HE variable overstates the HE expansion. Nevertheless, we conclude that our FRS HE variable picks up the main trends in education and is of reasonable quality.

Furthermore, there are two alternative education variables, which refer to the highest qualification achieved and that are available but only for two of the three waves in the analysis: variable 'edattn' in FRS 2007/08 and variable 'hi2qual' in FRS 2011/12. Edattn asks about the person's highest qualification, providing two choices – at degree level or above; or another kind of qualification. Hi2qual also asks about the highest qualification level providing 8 options, one of which is degree level or equivalent. Table 1.6 and Table 1.7 compare our education variable with these alternative variables where possible.[9] In contrast to the LFS validation, these both give lower estimates of the share with degree

[8] The variable on 'type of school or college attended' (variable 'typeed') also exists in all three waves but it has about 90% non-response in each wave for the sample of those aged 15-64.

[9] The comparison is done for the sample of individuals aged 15-64 with non-missing values for both my education and alternative FRS variables.

compared to the variable we use in the paper: 34.7% with FRS (our education variable) vs 28.6% with alternative FRS in 2007 (Table 1.6); and 38.4% with FRS vs 29.8% with alternative FRS in 2011 (Table 1.7). So, we have a mixed picture with the LFS comparison showing underestimation but the alternative FRS variables showing overestimation of the HE education levels.

Table 1.5:
Share of individuals with university degree

	shares			*% points change*	
	2001	2007	2011	2001-07	2007-11
LFS	25.9	28.7	33.2	2.8	4.5
FRS	22.1	27.9	31.7	5.8	3.8

Notes: LFS statistics refer to individuals with 'tertiary education (levels 5-8)' which includes: short-cycle tertiary education (level 5), bachelor's or equivalent level (level 6), master's or equivalent level (level 7) and doctoral or equivalent (level 8). Own derived variable with FRS includes individuals with undergraduate and postgraduate education (i.e. completed full-time education at the age of 19+). Sample is based on individuals aged 15-64.
Source: LFS statistics: Eurostat website, indicator edat_lfse_03, based on the Labour Force Survey.

Table 1.6:
Share of individuals by education attainment in 2007

	FRS	alternative FRS
not university	65.3	71.4
university	34.7	28.6

Notes: FRS (our education variable): category 'not university' includes those with secondary education and college; category 'university' includes undergraduate and postgraduate. Alternative FRS (variable 'edattn'): category 'not university' includes those who answered 'or another kind of qualification'; category 'university' includes those who answered 'at degree level or above'. Sample includes individuals aged 15 to 64 and with non-missing values for both variables. *Source:* Authors' calculations using the Family Resources Survey for 2007/08 (2007).

Table 1.7:
Share of individuals by education attainment in 2011

	FRS	alternative FRS
secondary	36.4	41.0
college	25.2	29.2
university	38.4	29.8

Notes: FRS (our education variable): category 'university' includes undergraduate and postgraduate. Alternative FRS (variable 'hi2qual'): category 'secondary' includes O Level/GCSE equivalent (Grade A-C) or O Grade/CSE equivalent (Grade 1) or Standard Grade level 1-3; GCSE grade D-G or CSE grade 2-5 or Standard Grade level 4-6; No formal qualifications; category 'college' includes Higher educational qualification below degree level; A-Levels or Highers; ONC/National Level BTEC; Other qualifications (including foreign qualifications below degree level); category 'university' includes Degree level qualification (or equivalent). Sample includes individuals aged 15 to 64 and with non-missing values for both variables.
Source: Authors' calculations using the Family Resources Survey for 2011/12 (2011).

Incomes

Incomes in the FRS are usually reported on a weekly basis but we convert them to monthly amounts, by multiplication of (52/12). Earnings are based on the variable 'ugrspay' (gross weekly pay from a job). The variable includes information on usual gross earnings, excluding income from odd jobs.

The measure of household net incomes used throughout the paper is:

+ earnings

+ self-employment income

+ investment income

+ private pensions

+ income from rent

+ private transfers paid to minus received from other households (e.g. maintenance payments)

+ incomes of children aged below 16

+ working families tax credit and disabled person in tax credit (in 2001)

+ working tax credit and child tax credit (in 2007 and 2011)

+ income support

+ pension credit (in 2007 and 2011)

+ housing benefit

+ council tax benefit

+ jobseeker's allowance (contributory and income-based)

+ student payments

+ student loans

+ attendance allowance

+ disability living allowance

+ disability living (mobility) allowance

+ incapacity benefit

+ contributory ESA

+ industrial injuries pension

+ invalid care allowance

+ severe disablement allowance

+ statutory sick pay

+ training allowance

+ statutory maternity pay

+ maternity allowance

+ winter fuel allowance

+ child benefit

+ retirement pension

+ occupational pension

+ war pension

+ widow pension

+ any other national insurance or state benefit

- personal income tax (including child tax credit in 2001)

- council tax

- employee and self-employed national insurance contributions

In-kind benefits (and indirect taxes) are disregarded as there is not enough information in the FRS which would allow to simulate these policies with EUROMOD. The same reason applies to certain tax deductions such as for mileage/motoring, union fees, loan repayments or charities which are not taken into account in EUROMOD simulations.

Sample adjustments

We adjust the data by dropping Northern Ireland and dropping the bottom 4% and top 1% of the net income distribution from the 2007/08 and 2011/12 waves. Table 1.8 shows sample sizes before and after the sample restrictions we impose on the FRS data:

Table 1.8:
Family Resources Survey

data wave	**original**	**adjusted**
2001/02		
n households	25,320	23,805
n individuals	59,499	56,496
2007/08		
n households	24,977	21,768
n individuals	56,926	49,875
2011/12		
n households	20,759	17,757
n individuals	47,744	41,042

Notes: The adjusted sample is derived after dropping individuals from Northern Ireland (from the 2007/08 and 2011/12 waves) and trimming the bottom 4% and top 1% of the household net income distribution.

1.8.3 Appendix C

In this section, first we show that what we infer about changes in the income distribution holds, regardless of whether we use simulated incomes (derived from EUROMOD simulations and FRS data) or reported incomes (based on FRS data only). Second, we explain in what ways our income estimates depart from the HBAI official statistics as well as the estimates by Jenkins (2017), using HBAI data.

To ensure that the baseline distributions of simulated and reported incomes are very close to each other, we compare various income statistics derived from reported vs simulated incomes. To make the comparisons meaningful, first we impose the same sample restrictions on the distributions of simulated and reported incomes, i.e. we drop households from Northern Ireland and trim the bottom 4% and top 1% of the respective income distributions. Second, we compare like with like: as we focus on cash-only incomes in our analysis, we constructed a variable for cash household net incomes using the FRS. Despite our best efforts, the definition of household net income is not completely identical using the simulated vs reported incomes since reported net incomes are net of certain deductions and tax on dividends and include tax rebates which could not be separated out from reported incomes and are not part of the simulated incomes.[10] We expect that these differences in the income definition will not cause large discrepancies between the two income distributions.

[10]The reason why these components are not simulated with EUROMOD is the lack of information in the FRS which allows the identification of i) individuals who are liable/entitled to such policies and ii) the amount which individuals are liable/entitled to.

In addition, there are other reasons which may lead to larger discrepancies between the distributions based on simulated and reported incomes. First, for any given year the policy rules simulated by EUROMOD are as of June, 30. The FRS data, on the other hand, collects from households information on benefits and taxes throughout the financial year.[11] Second, the FRS reported benefit incomes may be misreported for reasons such as stigma or recollection error. Third, there may be measurement error in the simulated incomes for the following reasons: the analyst may have made an error coding the policy rules; the information used in the calculations of benefits and taxes may suffer from measurement error (e.g. in earnings which enter benefit income-tests and are levied with taxes) or may not be available in the underlying FRS data (e.g. fuel expenditures used to calculate some tax deductions); tax evasion as well as tax avoidance are not taken into account in the personal tax simulations; benefit non-take-up may not be accurately modelled.[12]

Table 1.9 shows various income statistics derived from simulated incomes (EUROMOD with FRS) and reported incomes (FRS). As we analyse *changes* in the income distribution rather than levels, our primary interest lies with the last two columns of Table 1.9 which derive the difference in the estimates based on reported vs simulated incomes for the changes in the two periods (2001-07 and 2007-11) – we will refer to these as the difference-in-change estimates. We calculated bootstrapped standard errors for the difference-in-change estimates based on 1,000 replications. A bootstrap sample for each year is constructed by sampling households with replacement and by drawing samples of the same size as the raw unweighted data.

The key message from Table 1.9 is that the results for the changes in the income statistics based on both simulated and reported incomes are of very similar magnitude, with

[11] In contrast to benefits which are collected in much details in the FRS, there is no direct measure of personal incomes taxes or national insurance contributions in the FRS. The user can infer about their size by comparing gross with net income figures.

[12] Benefit calculations by EUROMOD are adjusted for non-take-up to reflect that some benefits may not be claimed by all entitled individuals/families/households. Different take-up proportions are applied by benefit and in some cases also by region or household type. Take-up rates are based on the mid-point estimates on a caseload basis published in the reports by the Department for Work and Pensions (DWP) and Her Majesty's Revenue and Customs (HMRC). DWP reports are available at: https://www.gov.uk/government/collections/income-related-benefits-estimates-of-take-up–2. HMRC reports are available at: https://www.gov.uk/government/collections/personal-tax-credits-and-child-benefit-finalised-award-statistics-take-up-rates. Take-up probabilities are randomly calculated at the household level and applied on the samples of eligible units.

some exceptions where the difference-in-change estimates are statistically significantly different from 0. Thus, what we infer about changes in the income distribution holds, regardless of whether we use simulated or reported incomes. In more detail, in the period 2001-07 the income growth at the bottom quintile/decile derived from simulated incomes is overstated compared to the estimate based on reported incomes and so does the drop in the 90/10 and 50/10 quintile ratios. However, if we look at the difference-in-change estimates for the Gini coefficient, population mean and the rest of quintile/decile medians, the estimates for the changes derived from simulated incomes are not statistically significantly different from those derived from reported incomes. For the period 2007-11, the income growth at the top of the distribution based on simulated incomes is somewhat overstated compared to the income change based on reported incomes. As a result, the difference-in-change in the 90/50 quintile ratio is statistically significant and so does the difference-in-change in the Gini (but only at the 10% significance level).

In the rest of the section, we comment on why our results based on simulated incomes depart from the official HBAI statistics as well as from the estimates by Jenkins (2017) using HBAI data. In comparison to us, Jenkins (2017) combines inequality estimates from HBAI survey and tax returns data to capture better inequality at top incomes. He notes that HBAI estimates, derived entirely from the FRS data, do not capture changes at the top of the income distribution which dominated the inequality trends in the 2000s (see also Jenkins, 2016, Burkhauser et al., 2016 and Belfield et al., 2014). In contrast to us, Jenkins finds an increase in the Gini between the mid-1990s and 2007 with most of the change occurring between 2004 and 2007 and driven by increased top income shares (see also Atkinson et al., 2011). Between 2007 and 2010, he finds a larger drop in inequality than us that is attributed to the introduction of the 50% marginal tax rate (see HM Revenue & Customs (2012) for analysis of the income 'forestalling' effects induced by the tax reform).

Our results depart from the official HBAI statistics and the estimates by Jenkins (2017) for the following reasons: First, we focus only on cash incomes. In comparison, the definition of household net incomes in HBAI includes the cash value of in-kind benefits (free school milk and meals and free TV license for those aged 75 and over) and certain

Table 1.9:
Comparing income statistics based on simulated vs reported incomes

	simulated incomes (EUROMOD with FRS)					reported incomes (FRS)					difference in estimates based on reported vs simulated incomes for the:	
	2001	2007	2011	% Δ in 2001-07	% Δ in 2001-07	2001/02	2007/08	2011/12	% Δ in 2001-07	% Δ in 2001-07	Δ in 2001-07	Δ in 2001-07
quintile medians in £												
Quintile 1	174	220	256	26.20	16.06	162	200	233	23.28	16.31	-2.92 ***	0.25
											(0.97)	(1.20)
Quintile 2	242	299	335	23.22	12.12	236	290	322	22.99	11.23	-0.23	-0.89
											(0.65)	(0.66)
Quintile 3 (population median)	326	397	435	22.04	9.35	321	394	431	22.51	9.47	0.47	0.12
											(0.53)	(0.56)
Quintile 4	431	528	576	22.52	9.17	433	535	580	23.61	8.36	1.09 **	-0.81
											(0.72)	(0.50)
Quintile 5	653	797	865	21.96	8.55	670	825	882	23.05	6.96	1.09	-1.59 **
											(0.96)	(0.80)
Ratio of top to bottom quintile medians (90/10 ratio)	3.74	3.62	3.38	-3.36	-6.46	4.13	4.12	3.79	-0.19	-8.04	3.17 ***	-1.57
											(0.96)	(1.09)
Ratio of top to median quintile medians (90/50 ratio)	2.01	2.00	1.99	-0.07	-0.72	2.09	2.09	2.05	0.44	-2.29	0.51	-1.57 **
											(0.71)	(0.78)
Ratio of median to bottom quintile medians (50/10 ratio)	1.87	1.80	1.70	-3.29	-5.78	1.98	1.97	1.85	-0.62	-5.88	2.67 ***	-0.10
											(0.86)	(0.98)
Gini coefficient	0.277	0.274	0.268	-0.93	-2.32	0.295	0.294	0.283	-0.28	-3.73	0.65	-1.41 *
											(0.44)	(0.84)
decile medians in £												
Decile 1	156	191	224	22.64	17.37	138	165	197	19.20	19.58	-3.44 **	2.21
											(1.55)	(1.90)
Decile 2	186	234	270	25.77	15.42	174	216	249	23.95	15.46	-1.82 **	0.04
											(0.85)	(0.94)
Decile 3	223	277	312	23.89	12.99	215	266	297	23.37	11.91	-0.52	-1.07
											(0.80)	(0.78)
Decile 4	261	322	358	23.41	11.29	256	314	348	22.78	10.68	-0.62	-0.61
											(0.63)	(0.61)
Decile 5	303	370	406	22.26	9.72	299	366	402	22.25	9.90	-0.01	0.18
											(0.52)	(0.57)
Decile 6	349	427	465	22.29	8.96	345	425	463	22.96	9.06	0.67	0.10
											(0.54)	(0.58)
Decile 7	400	491	536	22.51	9.27	401	493	540	22.97	9.53	0.46	0.26
											(0.51)	(0.55)
Decile 8	468	573	628	22.37	9.60	473	585	634	23.82	8.36	1.44 ***	-1.24 **
											(0.49)	(0.57)
Decile 9	577	701	764	21.48	9.04	590	724	782	22.54	8.09	1.06 *	-0.95
											(0.56)	(0.67)
Decile 10	803	978	1066	21.89	8.96	831	1018	1081	22.53	6.19	0.64	-2.77 **
											(0.94)	(1.23)
Population mean in £	383	469	518	22.58	10.41	383	470	514	22.71	9.21	0.13	-1.21 **
											(0.32)	(0.60)

Notes: Income amounts are weekly and equivalised using modified OECD equivalence scale (couple with no children as the reference). Significance levels indicated as $*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 1,002 replications.
Source: Authors' calculations using EUROMOD and the Family Resources Survey.

tax deductions (for mileage/motoring, union fees, loan repayments or charities) not simulated with EUROMOD. On the whole, we expect that these differences in the income concept will not matter much for the results. The next two reasons for departure are more important: the HBAI official statistics as well as estimates by Jenkins (2017) are based on the entire household sample of the FRS. To mitigate the risk of measurement error at the tails, we trim our sample by dropping the bottom 4% and top 1% of the income distribution. We also focus on households from Great Britain only and exclude those from Northern Ireland. Furthermore, HBAI incomes include imputations at the bottom (e.g. negative incomes are recoded to zero) and, more importantly, adjustments for individuals with very high incomes using the Survey of Personal Incomes (SPI). On the other hand, Jenkins (2017) combines inequality estimates from the HBAI survey and

SPI data to capture better inequality at top incomes. In contrast, we provide evidence on the income changes experienced by the middle 95% of the distribution but are oblivious to what happened at the tails.

1.8.4 Appendix D

This appendix presents the model specification for wages and the OLS regression results. In the wage models, education level (secondary, college, undergraduate, postgraduate) is interacted with age group (in 5 year bands). The vector of observable individual and household characteristics includes $x = \{1$, number of children in the household (1, 2, 3+), number of adults in the household (1, 2, 3+), being the head of the household, household average level of education, household average age, being in a couple, age group (in 5-year bands), skill level (low, middle, high), number of hours worked (in bands) and region$\}$. The estimation sample is restricted to employed workers aged 25 to 65 (males)/60 (females).

When analysing the periods 2001-07 and 2007-11, the regression model estimated on the workers sample from $t = 0$ is in fact estimated for $\ln \alpha y_{i(ht)}$ where α equals the Consumer Price Index (CPI) and $y_{i(ht)}$ are worker's earnings. The reason we adjust $y_{i(h0)}$ by CPI is because we need to bring $t = 0$ wage levels to $t = 1$ prices to construct the wage counterfactuals. Thus, when analysing the period 2001-07, the regression model for 2001 is in fact estimated on $\ln \alpha y_{i(h2001)}$ with α value of 1.1137 while that for 2007 is estimated for $\ln y_{i(h2007)}$. When analysing the period 2007-11, the regression model for 2007 is however estimated on $\ln \alpha y_{i(h2007)}$ with α equal to 1.1039 and the model for 2011 is estimated on $\ln y_{i(h2011)}$.

Table 1.10 and Table 1.11 present the OLS regression results for 2001 and 2007 for males and females, respectively. Table 1.12 and Table 1.13 show the OLS regression results for 2007 and 2011 male and female workers, respectively.

Table 1.10:
OLS log-earnings estimation results for males in 2001 and 2007

	2001 WB	2007 WB	2001 NWB	2007 NWB
Constant	7.239***	7.300***	6.843***	6.982***
	(.054)	(.068)	(.187)	(.158)
no children	ref	ref	ref	ref
1 child	-.021	.003	-.022	.072

	(.018)	(.021)	(.057)	(.051)
2 children	.015	.028	.053	.066
	(.022)	(.025)	(.078)	(.061)
3+ children	.010	.030	-.102	-.009
	(.029)	(.040)	(.083)	(.082)
1 adult	ref	ref	ref	ref
2 adults	-.017	.027	.119	.125*
	(.028)	(.029)	(.092)	(.066)
3+ adults	.033	.095***	.123	.136**
	(.025)	(.028)	(.101)	(.065)
head of the hh	.370***	.398***	.413***	.234***
	(.016)	(.020)	(.060)	(.045)
mean hh education: secondary	ref	ref	ref	ref
mean hh education:college	.095***	.085***	.069	.124**
	(.013)	(.017)	(.062)	(.058)
mean hh education:undergrad	.201***	.157***	.129	.226***
	(.025)	(.027)	(.079)	(.066)
mean hh education:postgrad	.294***	.235***	.290***	.321***
	(.037)	(.037)	(.086)	(.080)
average age in the hh	-.001	-.000	.003	.005*
	(.001)	(.001)	(.003)	(.003)
in a couple	.095***	.082***	.082	-.007
	(.023)	(.026)	(.092)	(.054)
working hours 50+	ref	ref	ref	ref
working hours 1-29	-1.168***	-1.198***	-1.245***	-1.224***
	(.048)	(.053)	(.088)	(.074)
working hours 30-39	-.149***	-.185***	-.206***	-.300***
	(.014)	(.021)	(.055)	(.048)
working hours 40-49	-.130***	-.141***	-.140**	-.206***
	(.013)	(.020)	(.059)	(.046)
age 40-44	ref	ref	ref	ref
age 25-29	-.155***	-.115***	-.509*	-.165*
	(.025)	(.030)	(.293)	(.092)
age 30-34	-.074***	-.116***	-.062	-.093
	(.021)	(.029)	(.084)	(.132)
age 35-39	-.054***	-.142***	-.087	-.092
	(.018)	(.027)	(.094)	(.092)
age 45-49	-.037*	-.076***	.028	-.040
	(.019)	(.024)	(.119)	(.110)
age 50-54	-.048**	-.095***	-.064	-.086
	(.021)	(.027)	(.099)	(.091)
age 55-59	-.097***	-.141***	-.242	.256*
	(.026)	(.035)	(.217)	(.131)
age 60-64	-.177***	-.190***	-.210*	.145
	(.031)	(.037)	(.116)	(.169)
aged 40-45 with secondary education	ref	ref	ref	ref
age 25-29 × college	-.014	-.118***	.508*	.001
	(.033)	(.037)	(.298)	(.119)
age 30-34 × college	-.045	-.088**	-.013	-.017
	(.029)	(.042)	(.106)	(.139)
age 35-39 × college	.085**	.084**	-.044	.069
	(.041)	(.037)	(.122)	(.102)
age 45-49 × college	.022	.057	.002	.083
	(.038)	(.040)	(.156)	(.126)
age 50-54 × college	.022	.090**	-.265	.053
	(.047)	(.044)	(.216)	(.168)
age 55-59 × college	-.010	.126**	.404	-.208
	(.082)	(.058)	(.260)	(.206)

age 60-64 × college	-.075	.065	-.200	.184
	(.096)	(.075)	(.211)	(.242)
age 25-29 × undergraduate	-.105**	-.034	.473	.048
	(.041)	(.053)	(.314)	(.104)
age 30-34 × undergraduate	-.013	-.027	.005	.100
	(.038)	(.048)	(.113)	(.145)
age 35-39 × undergraduate	.037	.190***	.167	.021
	(.047)	(.054)	(.141)	(.126)
age 45-49 × undergraduate	.074	.065	-.096	-.035
	(.053)	(.098)	(.199)	(.139)
age 50-54 × undergraduate	.127*	.173**	-.267	-.059
	(.065)	(.069)	(.196)	(.171)
age 55-59 × undergraduate	.033	.195**	.308	.098
	(.069)	(.093)	(.340)	(.224)
age 60-64 × undergraduate	-.053	-.054	.156	-.605*
	(.260)	(.200)	(.150)	(.362)
age 25-29 × postgraduate	-.152***	-.247***	.365	-.034
	(.048)	(.047)	(.314)	(.104)
age 30-34 × postgraduate	.010	.038	-.026	.004
	(.058)	(.048)	(.111)	(.146)
age 35-39 × postgraduate	.128**	.246***	.005	.051
	(.052)	(.054)	(.136)	(.120)
age 45-49 × postgraduate	.147**	.202***	-.083	.069
	(.066)	(.063)	(.148)	(.160)
age 50-54 × postgraduate	.081	.242**	-.374	.177
	(.059)	(.109)	(.244)	(.175)
age 55-59 × postgraduate	.091	.165**	.119	-.335
	(.081)	(.081)	(.241)	(.252)
age 60-64 × postgraduate	.010	.081	-.049	-.092
	(.163)	(.134)	(.157)	(.205)
low-skill	ref	ref		ref
undefined	.190	.479***		-.388
	(.227)	(.186)		(.431)
mid-skilled	.176***	.192***	.149**	.119***
	(.013)	(.017)	(.064)	(.038)
high-skilled	.526***	.518***	.679***	.637***
	(.015)	(.018)	(.052)	(.039)
London	ref	ref	ref	ref
North East	-.297***	-.240***	-.176	-.233
	(.030)	(.038)	(.140)	(.203)
North West	-.254***	-.284***	-.290***	-.193***
	(.025)	(.033)	(.068)	(.056)
Yorks and Humberside	-.297***	-.305***	-.151	-.148**
	(.025)	(.034)	(.097)	(.062)
East Midlands	-.250***	-.272***	-.103	-.232***
	(.025)	(.034)	(.086)	(.053)
West Midlands	-.237***	-.268***	-.170***	-.140**
	(.024)	(.036)	(.056)	(.059)
Eastern	-.119***	-.186***	-.091	-.104*
	(.025)	(.033)	(.086)	(.056)
South East	-.063***	-.128***	.042	-.116**
	(.024)	(.032)	(.054)	(.048)
South West	-.258***	-.253***	-.373***	-.161**
	(.026)	(.033)	(.098)	(.068)
Wales	-.303***	-.310***	-.320***	-.170**
	(.030)	(.037)	(.106)	(.081)
Scotland	-.248***	-.203***	-.645	-.096*

	(.026)	(.030)	(.401)	(.055)
R-squared	.479	.428	.458	.549
N	9012	7572	963	1164

Notes: *WB*=white British and *NWB*=non-white-British. Significance levels indicated as $*\quad p < 0.1$, $**\quad p < 0.05$, $***\quad p < 0.01$ and standard errors shown in parentheses. *Source:* Author's calculations using the Family Resources Survey.

Table 1.11:
OLS log-earnings estimation results for females in 2001 and 2007

	2001 WB	2007 WB	2001 NWB	2007 NWB
Constant	6.764***	7.065***	6.738***	6.766***
	(.097)	(.062)	(.213)	(.191)
no children	ref	ref	ref	ref
1 child	-.037	-.037*	.016	.003
	(.029)	(.021)	(.069)	(.062)
2 children	-.027	-.044*	-.008	-.029
	(.025)	(.025)	(.085)	(.079)
3+ children	-.069*	-.028	.065	.156
	(.038)	(.047)	(.107)	(.110)
1 adult	ref	ref	ref	ref
2 adults	.000	-.012	-.077	.014
	(.022)	(.022)	(.077)	(.060)
3+ adults	.008	-.015	-.018	.018
	(.024)	(.024)	(.080)	(.069)
head of the hh	.253***	.259***	.220***	.296***
	(.018)	(.016)	(.046)	(.043)
mean hh education: secondary	ref	ref	ref	ref
mean hh education:college	.090***	.080***	.075	.049
	(.020)	(.019)	(.069)	(.065)
mean hh education:undergrad	.188***	.159***	.142*	.081
	(.030)	(.031)	(.076)	(.064)
mean hh education:postgrad	.239***	.230***	.291***	.143*
	(.041)	(.037)	(.094)	(.081)
average age in the hh	.004***	.001	.005	.003
	(.001)	(.001)	(.004)	(.004)
in a couple	.161***	.179***	.104*	.045
	(.018)	(.019)	(.059)	(.049)
working hours 40+	ref	ref	ref	ref
working hours 1-15	-1.458***	-1.429***	-1.588***	-1.339***
	(.027)	(.034)	(.111)	(.098)
working hours 16-29	-.651***	-.683***	-.780***	-.599***
	(.019)	(.021)	(.073)	(.053)
working hours 30-39	-.088***	-.083***	-.038	-.077*
	(.016)	(.017)	(.043)	(.044)
age 40-44	ref	ref	ref	ref
age 25-29	-.015	-.064*	.100	-.093
	(.032)	(.035)	(.100)	(.108)
age 30-34	-.092	-.094***	.133	.054
	(.073)	(.034)	(.123)	(.156)
age 35-39	-.018	-.080***	.009	.136*
	(.023)	(.029)	(.126)	(.078)
age 45-49	-.065***	-.069***	-.049	.111
	(.021)	(.025)	(.092)	(.092)
age 50-54	-.146***	-.104***	-.138	-.064
	(.023)	(.027)	(.127)	(.097)

age 55-59	-.187***	-.144***	-.115	.012
	(.030)	(.031)	(.132)	(.136)
aged 40-45 with secondary education	ref	ref	ref	ref
age 25-29 × college	.010	-.081	-.344***	.121
	(.036)	(.051)	(.130)	(.129)
age 30-34 × college	.103	-.009	-.053	.102
	(.083)	(.050)	(.110)	(.176)
age 35-39 × college	.054*	.037	.083	-.071
	(.031)	(.044)	(.132)	(.087)
age 45-49 × college	-.007	.093***	-.166	-.062
	(.034)	(.035)	(.141)	(.105)
age 50-54 × college	.026	.010	.059	.269*
	(.050)	(.048)	(.139)	(.138)
age 55-59 × college	-.008	.057	-.040	-.099
	(.052)	(.047)	(.129)	(.143)
age 25-29 × undergraduate	.012	-.086*	-.067	.223*
	(.043)	(.050)	(.089)	(.122)
age 30-34 × undergraduate	.100	.099**	-.327**	-.017
	(.088)	(.048)	(.140)	(.160)
age 35-39 × undergraduate	-.012	.169**	-.029	-.089
	(.075)	(.072)	(.151)	(.092)
age 45-49 × undergraduate	.137***	.067	-.036	.025
	(.051)	(.063)	(.138)	(.173)
age 50-54 × undergraduate	.109**	.082	-.022	.158
	(.053)	(.056)	(.142)	(.129)
age 55-59 × undergraduate	.207***	.141*	.046	-.119
	(.059)	(.072)	(.190)	(.154)
age 25-29 × postgraduate	-.098**	-.126**	-.307***	-.112
	(.048)	(.051)	(.103)	(.138)
age 30-34 × postgraduate	.259***	.140***	-.030	.083
	(.088)	(.054)	(.134)	(.167)
age 35-39 × postgraduate	.200***	.162***	-.086	.028
	(.064)	(.056)	(.177)	(.124)
age 45-49 × postgraduate	.221***	.145**	-.034	-.150
	(.064)	(.069)	(.133)	(.148)
age 50-54 × postgraduate	.173***	.159*	.157	.137
	(.060)	(.083)	(.151)	(.170)
age 55-59 × postgraduate	.108	.187**	-.005	-.021
	(.138)	(.090)	(.244)	(.163)
low-skill	ref	ref		ref
undefined	.405**	.415***		.332**
	(.187)	(.114)		(.158)
mid-skilled	.221***	.221***	.164***	.303***
	(.020)	(.017)	(.050)	(.043)
high-skilled	.593***	.553***	.614***	.715***
	(.015)	(.016)	(.052)	(.045)
London	ref	ref	ref	ref
North East	-.212***	-.224***	-.129	-.168*
	(.074)	(.034)	(.116)	(.087)
North West	-.203***	-.263***	-.244***	-.270***
	(.069)	(.032)	(.081)	(.091)
Yorks and Humberside	-.189***	-.261***	-.198**	-.132
	(.071)	(.033)	(.082)	(.093)
East Midlands	-.185***	-.241***	-.202**	-.283***
	(.071)	(.033)	(.084)	(.063)
West Midlands	-.219***	-.230***	-.136**	-.223***
	(.070)	(.032)	(.064)	(.065)
Eastern	-.122*	-.204***	-.057	-.057

	(.069)	(.033)	(.072)	(.062)
South East	-.106	-.123***	-.041	-.152***
	(.068)	(.031)	(.060)	(.053)
South West	-.220***	-.276***	-.078	-.271***
	(.070)	(.035)	(.078)	(.092)
Wales	-.229***	-.347***	-.278**	-.247***
	(.070)	(.039)	(.128)	(.075)
Scotland	-.186***	-.217***	-.114	-.196***
	(.068)	(.029)	(.157)	(.050)
R-squared	.527	.621	.621	.567
N	8583	7221	851	1023

Notes: *WB*=white British and *NWB*=non-white-British. Significance levels indicated as $*\quad p < 0.1$, $**\quad p < 0.05$, $***\quad p < 0.01$ and standard errors shown in parentheses.
Source: Author's calculations using the Family Resources Survey.

Table 1.12:
OLS log-earnings estimation results for males in 2007 and 2011

	2007 WB	2011 WB	2007 NWB	2011 NWB
Constant	7.399***	7.389***	7.081***	7.043***
	(.068)	(.080)	(.158)	(.176)
no children	ref	ref	ref	ref
1 child	.003	.001	.072	.074
	(.021)	(.026)	(.051)	(.051)
2 children	.028	.060	.066	.129*
	(.025)	(.040)	(.061)	(.072)
3+ children	.030	.044	-.009	-.081
	(.040)	(.045)	(.082)	(.094)
1 adult	ref	ref	ref	ref
2 adults	.027	.090**	.125*	-.079
	(.029)	(.039)	(.066)	(.076)
3+ adults	.095***	.105***	.136**	-.076
	(.028)	(.036)	(.065)	(.070)
head of the hh	.398***	.367***	.234***	.323***
	(.020)	(.030)	(.045)	(.042)
mean hh education: secondary	ref	ref	ref	ref
mean hh education:college	.085***	.036*	.124**	.189***
	(.017)	(.021)	(.058)	(.070)
mean hh education:undergrad	.157***	.149***	.226***	.328***
	(.027)	(.031)	(.066)	(.075)
mean hh education:postgrad	.235***	.250***	.321***	.288***
	(.037)	(.042)	(.080)	(.081)
average age in the hh	-.000	-.000	.005*	.005
	(.001)	(.001)	(.003)	(.003)
in a couple	.082***	.023	-.007	.070
	(.026)	(.031)	(.054)	(.053)
working hours 50+	ref	ref	ref	ref
working hours 1-29	-1.198***	-1.136***	-1.224***	-1.262***
	(.053)	(.056)	(.074)	(.073)
working hours 30-39	-.185***	-.206***	-.300***	-.301***
	(.021)	(.025)	(.048)	(.064)
working hours 40-49	-.141***	-.167***	-.206***	-.260***
	(.020)	(.026)	(.046)	(.063)
age 40-44	ref	ref	ref	ref
age 25-29	-.115***	-.212***	-.165*	-.401**
	(.030)	(.045)	(.092)	(.165)

age 30-34	-.116***	-.168***	-.093	.046
	(.029)	(.037)	(.132)	(.104)
age 35-39	-.142***	-.102***	-.092	-.170*
	(.027)	(.038)	(.092)	(.097)
age 45-49	-.076***	.001	-.040	-.048
	(.024)	(.030)	(.110)	(.099)
age 50-54	-.095***	-.033	-.086	.152
	(.027)	(.035)	(.091)	(.096)
age 55-59	-.141***	-.037	.256*	-.081
	(.035)	(.039)	(.131)	(.131)
age 60-64	-.190***	-.128***	.145	-.129
	(.037)	(.041)	(.169)	(.148)
aged 40-45 with secondary education	ref	ref	ref	ref
age 25-29 × college	-.118***	-.060	.001	.310*
	(.037)	(.056)	(.119)	(.187)
age 30-34 × college	-.088**	.036	-.017	-.296**
	(.042)	(.048)	(.139)	(.124)
age 35-39 × college	.084**	.031	.069	-.002
	(.037)	(.054)	(.102)	(.122)
age 45-49 × college	.057	.020	.083	.074
	(.040)	(.048)	(.126)	(.135)
age 50-54 × college	.090**	.143**	.053	-.297**
	(.044)	(.058)	(.168)	(.126)
age 55-59 × college	.126**	.123**	-.208	-.244
	(.058)	(.060)	(.206)	(.159)
age 60-64 × college	.065	-.088	.184	-.116
	(.075)	(.124)	(.242)	(.209)
age 25-29 × undergraduate	-.034	-.019	.048	.214
	(.053)	(.056)	(.104)	(.172)
age 30-34 × undergraduate	-.027	.087	.100	-.303***
	(.048)	(.059)	(.145)	(.116)
age 35-39 × undergraduate	.190***	.049	.021	-.044
	(.054)	(.068)	(.126)	(.126)
age 45-49 × undergraduate	.065	.142*	-.035	.045
	(.098)	(.084)	(.139)	(.156)
age 50-54 × undergraduate	.173**	.090	-.059	-.204
	(.069)	(.074)	(.171)	(.185)
age 55-59 × undergraduate	.195**	-.000	.098	.030
	(.093)	(.108)	(.224)	(.181)
age 60-64 × undergraduate	-.054	.024	-.605*	-.204
	(.200)	(.113)	(.362)	(.206)
age 25-29 × postgraduate	-.247***	-.133**	-.034	.231
	(.047)	(.065)	(.104)	(.172)
age 30-34 × postgraduate	.038	.080	.004	-.102
	(.048)	(.066)	(.146)	(.115)
age 35-39 × postgraduate	.246***	.275**	.051	.223*
	(.054)	(.131)	(.120)	(.124)
age 45-49 × postgraduate	.202***	.071	.069	.064
	(.063)	(.086)	(.160)	(.153)
age 50-54 × postgraduate	.242**	.394***	.177	-.399*
	(.109)	(.086)	(.175)	(.222)
age 55-59 × postgraduate	.165**	.093	-.335	-.406**
	(.081)	(.074)	(.252)	(.182)
age 60-64 × postgraduate	.081	.054	-.092	-.017
	(.134)	(.134)	(.205)	(.251)
low-skilled	ref	ref	ref	ref
undefined	.479***	.099	-.388	.734***
	(.186)	(.093)	(.431)	(.072)

mid-skilled	.192***	.171***	.119***	.159***
	(.017)	(.020)	(.038)	(.040)
high-skilled	.518***	.520***	.637***	.682***
	(.018)	(.022)	(.039)	(.042)
London	ref	ref	ref	ref
North East	-.240***	-.320***	-.233	-.195**
	(.038)	(.051)	(.203)	(.087)
North West	-.284***	-.245***	-.193***	-.160***
	(.033)	(.040)	(.056)	(.059)
Yorks and Humberside	-.305***	-.259***	-.148**	-.143*
	(.034)	(.042)	(.062)	(.080)
East Midlands	-.272***	-.292***	-.232***	-.044
	(.034)	(.045)	(.053)	(.065)
West Midlands	-.268***	-.265***	-.140**	-.230***
	(.036)	(.041)	(.059)	(.063)
Eastern	-.186***	-.123**	-.104*	-.161***
	(.033)	(.058)	(.056)	(.061)
South East	-.128***	-.149***	-.116**	.036
	(.032)	(.042)	(.048)	(.054)
South West	-.253***	-.227***	-.161**	-.081
	(.033)	(.042)	(.068)	(.086)
Wales	-.310***	-.320***	-.170**	-.157
	(.037)	(.047)	(.081)	(.103)
Scotland	-.203***	-.187***	-.096*	-.102
	(.030)	(.038)	(.055)	(.073)
R-squared	.428	.426	.549	.580
N	7572	5915	1164	1106

Notes: *WB*=white British and *NWB*=non-white-British. Significance levels indicated as $*\quad p < 0.1$, $**\quad p < 0.05$, $***\quad p < 0.01$ and standard errors shown in parentheses.
Source: Author's calculations using the Family Resources Survey.

Table 1.13:
OLS log-earnings estimation results for females in 2007 and 2011

	2007 WB	2011 WB	2007 NWB	2011 NWB
Constant	7.164***	6.990***	6.864***	6.786***
	(.062)	(.100)	(.191)	(.193)
no children	ref	ref	ref	ref
1 child	-.037*	-.083***	.003	-.013
	(.021)	(.026)	(.062)	(.057)
2 children	-.044*	-.023	-.029	-.062
	(.025)	(.039)	(.079)	(.090)
3+ children	-.028	-.227***	.156	.008
	(.047)	(.053)	(.110)	(.119)
1 adult	ref	ref	ref	ref
2 adults	-.012	.097***	.014	.132*
	(.022)	(.030)	(.060)	(.078)
3+ adults	-.015	.116***	.018	.045
	(.024)	(.032)	(.069)	(.079)
head of the hh	.259***	.334***	.296***	.285***
	(.016)	(.025)	(.043)	(.043)
mean hh education: secondary	ref	ref	ref	ref
mean hh education:college	.080***	.022	.049	-.041
	(.019)	(.059)	(.065)	(.071)
mean hh education:undergrad	.159***	.167***	.081	.108
	(.031)	(.056)	(.064)	(.080)

mean hh education:postgrad	.230***	.330***	.143*	.183*
	(.037)	(.085)	(.081)	(.095)
average age in the hh	.001	.001	.003	.006*
	(.001)	(.002)	(.004)	(.003)
in a couple	.179***	.167***	.045	.047
	(.019)	(.024)	(.049)	(.050)
working hours 40+	ref	ref	ref	ref
working hours 1-15	-1.429***	-1.324***	-1.339***	-1.395***
	(.034)	(.041)	(.098)	(.123)
working hours 16-29	-.683***	-.629***	-.599***	-.700***
	(.021)	(.030)	(.053)	(.065)
working hours 30-39	-.083***	-.049**	-.077*	-.069
	(.017)	(.022)	(.044)	(.045)
age 40-44	ref	ref	ref	ref
age 25-29	-.064*	-.153***	-.093	-.113
	(.035)	(.053)	(.108)	(.207)
age 30-34	-.094***	-.138**	.054	.048
	(.034)	(.062)	(.156)	(.134)
age 35-39	-.080***	-.092**	.136*	-.071
	(.029)	(.040)	(.078)	(.095)
age 45-49	-.069***	-.107***	.111	.136
	(.025)	(.035)	(.092)	(.116)
age 50-54	-.104***	-.091***	-.064	-.237*
	(.027)	(.034)	(.097)	(.125)
age 55-59	-.144***	-.205**	.012	-.113
	(.031)	(.092)	(.136)	(.104)
aged 40-45 with secondary education	ref	ref	ref	ref
age 25-29 × college	-.081	-.002	.121	-.041
	(.051)	(.068)	(.129)	(.249)
age 30-34 × college	-.009	.054	.102	-.013
	(.050)	(.075)	(.176)	(.149)
age 35-39 × college	.037	.064	-.071	.284*
	(.044)	(.058)	(.087)	(.148)
age 45-49 × college	.093***	.060	-.062	-.106
	(.035)	(.050)	(.105)	(.127)
age 50-54 × college	.010	.116**	.269*	.354**
	(.048)	(.054)	(.138)	(.148)
age 55-59 × college	.057	.107	-.099	-.187
	(.047)	(.129)	(.143)	(.167)
age 25-29 × undergraduate	-.086*	-.046	.223*	-.166
	(.050)	(.065)	(.122)	(.219)
age 30-34 × undergraduate	.099**	.115	-.017	-.054
	(.048)	(.076)	(.160)	(.170)
age 35-39 × undergraduate	.169**	.069	-.089	.043
	(.072)	(.068)	(.092)	(.128)
age 45-49 × undergraduate	.067	.207***	.025	.048
	(.063)	(.066)	(.173)	(.157)
age 50-54 × undergraduate	.082	.147**	.158	.090
	(.056)	(.064)	(.129)	(.164)
age 55-59 × undergraduate	.141*	.271**	-.119	.028
	(.072)	(.135)	(.154)	(.130)
age 25-29 × postgraduate	-.126**	-.175**	-.112	-.078
	(.051)	(.084)	(.138)	(.218)
age 30-34 × postgraduate	.140***	.013	.083	-.055
	(.054)	(.091)	(.167)	(.164)
age 35-39 × postgraduate	.162***	.026	.028	.191
	(.056)	(.084)	(.124)	(.123)
age 45-49 × postgraduate	.145**	.266***	-.150	-.077

	(.069)	(.080)	(.148)	(.173)
age 50-54 × postgraduate	.159*	-.004	.137	.020
	(.083)	(.107)	(.170)	(.178)
age 55-59 × postgraduate	.187**	.135	-.021	-.052
	(.090)	(.151)	(.163)	(.179)
low-skilled	ref		ref	ref
undefined	.415***		.332**	-.591
	(.114)		(.158)	(.580)
mid-skilled	.221***	.239***	.303***	.218***
	(.017)	(.027)	(.043)	(.051)
high-skilled	.553***	.582***	.715***	.622***
	(.016)	(.025)	(.045)	(.046)
London	ref	ref	ref	ref
North East	-.224***	-.219***	-.168*	-.110
	(.034)	(.043)	(.087)	(.154)
North West	-.263***	-.277***	-.270***	-.116
	(.032)	(.061)	(.091)	(.074)
Yorks and Humberside	-.261***	-.210***	-.132	-.057
	(.033)	(.042)	(.093)	(.085)
East Midlands	-.241***	-.216***	-.283***	-.210**
	(.033)	(.040)	(.063)	(.082)
West Midlands	-.230***	-.200***	-.223***	-.287***
	(.032)	(.038)	(.065)	(.096)
Eastern	-.204***	-.121**	-.057	-.184**
	(.033)	(.053)	(.062)	(.073)
South East	-.123***	-.153***	-.152***	-.068
	(.031)	(.038)	(.053)	(.049)
South West	-.276***	-.247***	-.271***	-.233**
	(.035)	(.040)	(.092)	(.114)
Wales	-.347***	-.225***	-.247***	-.202*
	(.039)	(.046)	(.075)	(.115)
Scotland	-.217***	-.161***	-.196***	-.071
	(.029)	(.037)	(.050)	(.094)
R-squared	.621	.447	.567	.563
N	7221	5810	1023	962

Notes: *WB*=white British and *NWB*=non-white-British. Significance levels indicated as $*\quad p < 0.1$, $**\quad p < 0.05$, $***\quad p < 0.01$ and standard errors shown in parentheses.
Source: Author's calculations using the Family Resources Survey.

1.8.5 Appendix E

In this section, we explore the change in mean household equivalised net incomes across subgroups in 2001-07 (Table 1.14) and 2007-11 (Table 1.15). Between 2001 and 2007, all subgroups (apart from lone father households) saw their real incomes rising on average but some benefited more than others (Table 1.14). The largest income gains were for children (10%), pensioners including single households and pensioner couples (11-13%), and lone mother households (13%).

For most subgroups the TBP effect was positive (with a small negative effect only for couples without children) but the gains were always outweighed by the PCMI effect (with the exception of lone father households). The average income gain (column 'all') from the PCMI effect was 8% (compared to 0.3% due to tax-benefit policy changes) and the largest gains of more than 9% were enjoyed by children, couples with children, pensioners and pensioner couples. The average for the population income gain due to wages was 2.4% with the biggest income increases of more than 3% for couples without children. On the other hand, compared to other groups which were favoured by TBP changes, this subgroup lost slightly from the changes to tax-benefit policies. As a result, their relative position in the income distribution worsened, or in other words, tax-benefit policies helped narrowing the gap between them and the other relatively poorer subgroups.

The gains from education composition changes were somewhat bigger at 3.8% for the total population and for most groups exceeding the gains from wages as the positive education effects not only fed through wages but also other sources of gross market income such as investment income and private pensions. For example, although pensioners did not benefit from the real growth in wages, they benefited from HE expansion as the higher number of more educated pensioners meant also higher pensions (despite the short time span of 7 years we are looking at). In particular, looking at individuals aged 50 and above (capturing early retirees as well), the share of those with post-secondary education increased by 30% while the share of HE degree holders rose by 38% between 2001 and 2007. HE expansion raised by more than 4% the incomes of couples with children and children (since we look at equivalised household incomes), non-white-British and Londoners.

As the HE income gains – mostly through higher earnings – for working-age females and non-white-British exceeded the gains for working-age males and white British respectively, income inequality between sex and ethnic groups fell, all else being equal. Hence, although education composition changes increased overall inequality, they pushed down between-inequality among some subgroups.

In contrast to the boom period when almost all subgroups gained on average, the crisis period 2007-11 is a mixed picture of gainers and losers (Table 1.15). Despite no change in the population mean household income, there was quite a lot of heterogeneity among subgroups. The biggest gainers with a real income increase of more than 4% were pensioners, including single female households and pensioner couples, lone mother and lone father households. For these subgroups, changes to TBP and PCMI both worked to increase their incomes. On the other hand, for all losers (with the largest statistically significant loss of 2.5% for couples without children) it was the PCMI effect which reduced their incomes. Although the returns to individual and household characteristics with respect to wages (apart from those to HE) fell throughout most of the income distribution, they did not affect average incomes. Increase in HE attainment continued to benefit all subgroups in the crisis years. The average income gain was slightly lower at 3% compared to average 3.8% income gain in the growth period. Interestingly, the same subgroups as in the earlier period continued to experience among the largest income gains, i.e. children and couples with children, non-white-British and Londoners. Finally, in both periods the wage returns to HE remained broadly constant with no effect on subgroup average incomes.

Table 1.14:

Change in mean income (in %) between 2001 and 2007, by subgroups

	all	child	wam	waf	mp	fp	swm	swf	smp	sfp
total change	8.631***	10.334***	6.761***	7.655***	12.037***	12.984***	4.454*	6.053**	10.743***	11.550***
	(.3)	(.6)	(.5)	(.5)	(1.0)	(.8)	(1.8)	(2.1)	(1.9)	(1.1)
PCMI effect	8.383***	9.401***	7.343***	8.011***	8.970***	10.207***	4.561***	6.462***	6.175***	7.325***
	(.2)	(.5)	(.4)	(.4)	(.7)	(.6)	(1.3)	(1.5)	(1.4)	(.8)
iv) changes to wages	2.402***	2.266***	2.890***	2.702***	.263	1.081	1.505	1.973	.060	.706
	(.2)	(.5)	(.4)	(.4)	(.8)	(.6)	(1.4)	(1.6)	(1.4)	(.9)
v) changes to returns to HE: wBm	.410	.472	.542	.414	.003	.050	.767	.000	-.000	.009
	(.2)	(.5)	(.4)	(.4)	(.8)	(.6)	(1.4)	(1.7)	(1.4)	(.9)
vi) changes to returns to HE: nwBm	-.091	.022	-.203	-.081	.007	.035	-.139	.000	-.000	.079
	(.2)	(.5)	(.4)	(.4)	(.8)	(.6)	(1.3)	(1.7)	(1.4)	(.9)
vii) changes to returns to HE: wBf	-.143	-.025	-.161	-.256	-.011	.016	.000	-.766	-.000	.081
	(.2)	(.5)	(.4)	(.4)	(.8)	(.6)	(1.3)	(1.7)	(1.4)	(.9)
viii) changes to returns to HE: nwBf	.198	.188	.209	.282	.012	.012	.165	.506	-.000	.009
	(.2)	(.5)	(.4)	(.4)	(.8)	(.6)	(1.3)	(1.7)	(1.4)	(.9)
ix) changes to education composition	3.832***	5.307***	3.181***	3.862***	2.068**	3.240***	1.185	4.111*	.199	1.899*
	(.2)	(.5)	(.4)	(.4)	(.8)	(.6)	(1.3)	(1.6)	(1.4)	(.8)
x) residual	1.776***	1.171**	.884*	1.088**	6.628***	5.772***	1.079	.638	5.916***	4.542***
	(.2)	(.4)	(.4)	(.4)	(.7)	(.5)	(1.3)	(1.5)	(1.4)	(.8)
TBP effect	.248	.933	-.582	-.356	3.067***	2.777***	-.107	-.409	4.568***	4.226***
	(.2)	(.5)	(.4)	(.4)	(.7)	(.6)	(1.3)	(1.5)	(1.4)	(.8)

cont.

	lmh	lfh	c0c	cc	pc	ohh	wb	nwb	l	e
total change	13.000***	-3.945	7.558***	8.848***	13.399***	2.274	8.815***	8.321***	7.535***	8.814***
	(.8)	(3.4)	(.5)	(.5)	(.8)	(1.3)	(.3)	(1.0)	(.8)	(.3)
PCMI effect	8.267***	-6.710**	8.472***	9.093***	10.712***	2.175*	8.584***	7.898***	7.908***	8.451***
	(.5)	(2.4)	(.4)	(.3)	(.6)	(.9)	(.2)	(.7)	(.6)	(.2)
iv) changes to wages	1.834**	-1.694	3.007***	2.647***	.256	3.076**	2.740***	.428	.828	2.699***
	(.6)	(2.5)	(.4)	(.4)	(.7)	(1.0)	(.3)	(.8)	(.6)	(.3)
v) changes to returns to HE: wBm	.006	.186	.480	.573	-.001	.263	.419	.360	.599	.374
	(.6)	(2.7)	(.4)	(.4)	(.7)	(.9)	(.3)	(.8)	(.6)	(.3)
vi) changes to returns to HE: nwBm	.073	.164	-.198	-.010	.008	-.274	.005	-.663	-.026	-.104
	(.6)	(2.7)	(.4)	(.4)	(.7)	(.9)	(.3)	(.8)	(.6)	(.3)
vii) changes to returns to HE: wBf	-.060	-.000	-.265	-.056	-.012	-.149	-.157	-.060	-.056	-.161
	(.6)	(2.7)	(.4)	(.4)	(.7)	(.9)	(.3)	(.8)	(.6)	(.3)
viii) changes to returns to HE: nwBf	.165	-.000	.238	.221	.006	.208	.048	1.084	.227	.192
	(.6)	(2.7)	(.4)	(.4)	(.7)	(.9)	(.3)	(.8)	(.6)	(.3)
ix) changes to education composition	3.220***	1.394	3.037***	4.987***	2.876***	1.383	3.687***	4.983***	4.366***	3.636***
	(.6)	(2.5)	(.4)	(.4)	(.6)	(.9)	(.2)	(.7)	(.6)	(.3)
x) residual	3.030***	-6.762**	2.173***	.731*	7.579***	-2.330*	1.842***	1.765*	1.971***	1.814***
	(.5)	(2.4)	(.4)	(.3)	(.6)	(.9)	(.2)	(.7)	(.6)	(.2)
TBP effect	4.733***	2.765	-.914*	-.244	2.687***	.098	.231	.423	-.373	.362
	(.6)	(2.3)	(.4)	(.4)	(.6)	(1.0)	(.2)	(.7)	(.6)	(.2)

Notes: PCMI=population characteristics and market incomes; TBP=tax-benefit policies; all=all households, child=child, wam=working-age male, waf = working-age female, mp=male pensioner, fp=female pensioner; swm=single household-working-age male, swf=single household-working-age female, smp=single household-male pensioner, sfp=single household-female pensioner, lmh=lone mother household, lfh=lone father household, c0c=(non-pensioner) couple with no children, cc=couple with children, pc=pensioner couple, ohh=other household types; wb=white British, nwb=non-white-British; l=living in London, e=living elsewhere. A child is defined as an individual aged less than 16. A working-age is an individual aged 16+ and less than 60 (female)/65 (male). A pensioner is someone aged 60+ (female)/65+ (male). Standard errors are estimated using the delta method (Taylor approximations). Significance levels indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' calculations using EUROMOD and the Family Resources Survey.

Table 1.15:

Change in mean income (in %) between 2007 and 2011, by subgroups

	all	child	wam	waf	mp	fp	swm	swf	smp	sfp
total change	.080	2.025*	-1.651*	-2.284**	7.328***	7.147***	-.908	-4.965	3.948	5.760***
	(.4)	(.9)	(.7)	(.7)	(1.4)	(1.1)	(2.6)	(2.8)	(2.6)	(1.6)
PCMI effect	-1.581***	-.032	-2.976***	-3.627***	4.362***	4.449***	-3.359	-6.458**	1.557	3.093**
	(.3)	(.6)	(.5)	(.5)	(.9)	(.8)	(1.8)	(2.0)	(1.9)	(1.1)
iv) changes to wages	-.245	-.235	-.472	-.303	.443	.303	-.318	.037	1.017	-.141
	(.3)	(.7)	(.5)	(.5)	(1.0)	(.8)	(2.0)	(2.2)	(2.0)	(1.1)
v) changes to returns to HE: wBm	.060	.051	.085	.059	.019	.024	-.008	.018	.000	-.000
	(.3)	(.7)	(.5)	(.5)	(1.0)	(.8)	(2.0)	(2.1)	(2.0)	(1.1)
vi) changes to returns to HE: nwBm	-.053	-.106	-.074	-.050	.028	.032	-.196	.161	.000	-.000
	(.3)	(.7)	(.5)	(.5)	(1.0)	(.8)	(2.0)	(2.1)	(2.0)	(1.1)
vii) changes to returns to HE: wBf	-.079	-.125	-.079	-.100	.011	-.001	.000	-.451	.000	-.000
	(.3)	(.7)	(.5)	(.5)	(1.0)	(.8)	(2.0)	(2.1)	(2.0)	(1.1)
viii) changes to returns to HE: nwBf	-.043	.083	-.063	-.103	-.010	-.007	-.101	-.108	.000	-.000
	(.3)	(.7)	(.5)	(.5)	(1.0)	(.8)	(2.0)	(2.1)	(2.0)	(1.1)
ix) changes to education composition	3.083***	4.863***	2.828***	2.553***	2.705**	3.486***	1.563	.589	1.553	1.595
	(.3)	(.6)	(.5)	(.5)	(.9)	(.8)	(2.0)	(2.0)	(1.9)	(1.1)
x) residual	-4.304***	-4.563***	-5.201***	-5.681***	1.166	.612	-4.299*	-6.704***	-1.013	1.639
	(.3)	(.6)	(.5)	(.5)	(.9)	(.7)	(1.8)	(1.8)	(1.7)	(1.1)
TBP effect	1.661***	2.058**	1.325*	1.343*	2.965**	2.698***	2.450	1.493	2.392	2.667*
	(.3)	(.6)	(.5)	(.5)	(.9)	(.8)	(1.9)	(2.1)	(1.9)	(1.1)

cont.

	lmh	lfh	c0c	cc	pc	ohh	wb	nwb	l	e
total change	6.616***	11.629**	-2.502***	.479	8.364***	-4.090*	.360	-.900	-.889	.258
	(1.1)	(4.4)	(.7)	(.7)	(1.2)	(1.6)	(.4)	(1.2)	(1.1)	(.4)
PCMI effect	2.136**	9.101**	-3.974***	-.958*	5.117***	-3.243**	-1.392***	-2.084*	-1.881*	-1.536***
	(.8)	(3.1)	(.5)	(.5)	(.8)	(1.1)	(.3)	(.9)	(.8)	(.3)
iv) changes to wages	-.299	3.419	-.391	-.378	.362	-.263	-.120	-.886	-.550	-.187
	(.8)	(3.2)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)
v) changes to returns to HE: wBm	-.064	-.265	.064	.067	.034	.225	.055	.090	-.029	.078
	(.8)	(2.9)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)
vi) changes to returns to HE: nwBm	-.002	.126	-.008	-.146	-.007	.019	.046	-.566	.051	-.073
	(.8)	(2.9)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)
vii) changes to returns to HE: wBf	.064	.000	-.072	-.147	-.007	.008	-.080	-.077	-.151	-.064
	(.8)	(2.9)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)
viii) changes to returns to HE: nwBf	.062	.000	-.157	.080	.007	-.172	-.038	-.066	-.118	-.028
	(.8)	(2.9)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)
ix) changes to education composition	2.515**	5.174	1.899***	5.360***	2.684***	1.667	2.994***	3.818***	3.380***	2.954***
	(.8)	(3.0)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)
x) residual	-.141	.648	-5.309***	-5.796***	2.045**	-4.727***	-4.249***	-4.397***	-4.464***	-4.215***
	(.7)	(2.7)	(.5)	(.4)	(.8)	(1.1)	(.3)	(.8)	(.7)	(.3)
TBP effect	4.481***	2.527	1.473**	1.437**	3.246***	-.847	1.752***	1.184	.993	1.793***
	(.8)	(3.1)	(.5)	(.5)	(.8)	(1.2)	(.3)	(.9)	(.8)	(.3)

Notes: PCMI=population characteristics and market incomes; TBP=tax-benefit policies; all=all households, child=child, wam=working-age male, waf = working-age female, mp=male pensioner, fp=female pensioner; swm=single household-woorking-age male, swf=single household-working-age female, smp=single household-male pensioner, sfp=single household-female pensioner, lmh=lone mother household, lfh=lone father household, c0c=(non-pensioner) couple with no children, cc=couple with children, pc=pensioner couple, ohh=other household types; wb=white British, nwb=non-white-British; l=living in London, e=living elsewhere. A child is defined as an individual aged less than 16. A working-age is an individual aged 16+ and less than 60 (female)/65 (male). A pensioner is someone aged 60+ (female)/65+ (male). Standard errors are estimated using the delta method (Taylor approximations). Significance levels indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: Authors' calculations using EUROMOD and the Family Resources Survey.

Chapter 2

Europe Through the Crisis: Discretionary Policy Changes and Automatic Stabilisers[1]

(co-authored with Alari Paulus)

Abstract

Tax-benefit policies affect changes in household incomes through two main channels: discretionary policy changes and automatic stabilisers. Although a large body of literature has studied the impact of tax-benefit policy changes on incomes, little is known about the link between automatic stabilisers and the income distribution. We contribute to the literature by studying in detail the contribution of automatic stabilisers and discretionary policy changes to income changes in the EU countries between 2007 and 2014. Our results show that, discretionary policy changes and the automatic stabilisation response of policies more often worked to reduce rather than increase inequality of net incomes, and so helped offset the inequality-increasing impact

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of a growing disparity in gross (pre-tax) market incomes. Inequality reduction was achieved mainly through benefits using both routes. On the other hand, policy changes to and the automatic stabilisation response of taxes and social insurance contributions raised inequality in some countries and lowered it in others.

Keywords: automatic stabilisers, discretionary policy changes, income distribution, decomposition

JEL codes: D31, H23, E63

2.1 Introduction

The financial crisis of 2007-08 and the subsequent Great Recession posed serious economic challenges to Europe. Substantial increases to unemployment, losses to wages and self-employment income, increase in governments debt and fall in GDP put strain on fiscal budgets and households finances.[2] In response to such economic challenges, tax-benefit policies have important implications for household net incomes. They affect incomes through two main channels: discretionary policy changes and automatic stabilisers.

Automatic stabilisers characterise the policies' in-built flexibility to absorb shocks to earnings and people's characteristics (Pechman, 1973). They reduce, ceteris paribus, the need for discretionary policy actions which take time to design and implement and can be particularly important if the scope for discretionary fiscal policies is limited, e.g. in the eurozone (Mabbett and Schelkle, 2007). They are viewed as a crucial tool for reducing macroeconomic volatility (e.g. Blanchard et al. 2010). In particular, income taxes and unemployment insurance benefits in the US, Canada and Europe have received a lot of attention from the micro and macro literature as important stabilisers of fluctuations of aggregate output as well as of disposable income and household consumption (e.g. Auerbach and Feenberg, 2000; Browning and Crossley, 2001; Kniesner and Ziliak, 2002; Auerbach, 2009; Dolls et al., 2012; Salgado et al., 2014; Di Maggio and Kermani, 2016; McKay and Reis, 2016; Hsu et al., 2018).

There is less consensus on the size and direction of impact of discretionary fiscal policies on economic stability (e.g. Taylor, 2000; Feldstein, 2002; Blanchard and Perotti, 2002; Fatás and Mihov, 2003; Auerbach and Gorodnichenko, 2012; Caggiano et al., 2015; Miyamoto et al., 2018). But a large body of micro literature has shown their importance for the income distribution, for example, Clark and Leicester (2005), Sefton and Sutherland (2005), Sutherland et al. (2008) and Bargain (2012b) for the UK; Decoster et al. (2015) for Belgium; Hills et al. (2019), Paulus et al. (forthcoming), Matsaganis and Leventi (2014), De Agostini et al. (2016) and Bargain et al. (2017) for selected EU

[2] Between 2007 and 2014, GDP fell in 10 EU countries although it increased in the EU-28 on average (+1.5%). Government debt as % of GDP increased in every EU member state and overall by a staggering 51%. The effect on households was equally severe: the share of unemployed (as a % of the population) increased in all EU countries, except Germany, and overall by 44%. Real wages and salaries, the main source of household income, fell by 4.4%, while income from self-employment dropped by nearly 10% on average. See Eurostat database.

countries. A decomposition approach combined with a tax-benefit calculator and household micro-data has enabled researchers to identify the direct (non-behavioural) impact of policy changes on the income distribution. The estimate for the policy effect has often been compared with the contribution of 'other' factors, which encompass the *combined* (net) effect of changes to market incomes and population characteristics, and automatic stabilisers (e.g. Bargain and Callan, 2010; Bargain et al., 2015, 2017). For the early crisis years (2007-11), the literature agrees that policy changes were broadly poverty- and inequality-reducing in most/all countries but their redistributive effect became more heterogeneous across countries between 2011 and 2014.

In contrast, there is little empirical evidence on the redistributive power of automatic stabilisers. For several Southern EU countries and Ireland, Callan et al. (2018) find that automatic stabilisers – mainly through benefits – reduced income inequality between 2007 and 2013. For Great Britain, Tasseva (2018) (Chapter 1 in this thesis) finds that pro-rich income gains due to education changes were mitigated by automatic stabilisers. For hypothetical earnings shocks, on the other hand, benefits and taxes are shown to stabilise mostly the incomes of households at the bottom and top of the distribution, respectively (European Commission, 2017); while Dolls et al. (2011) find that households located at the bottom of the distribution are least protected by policies against shocks.

We aim to contribute to improved understanding of the link between automatic stabilisers and the income distribution by providing an in-depth account of the relative impact of automatic stabilisers and discretionary policy changes on household incomes in the EU in recent years (2007-2014), covering the latest economic crisis and post-crisis economic developments. We seek to decompose observed changes in the income distribution into changes due to: i) discretionary tax-benefit policy changes, ii) the automatic stabilisation response of tax-benefit policies, and iii) gross (pre-tax) market incomes and population changes. Keeping fixed gross market incomes and population characteristics, tax-benefit policy changes encompass changes to the design of the tax-benefit system and the statutory uprating of/discretionary (ad-hoc) changes to monetary parameters, such as benefit amounts and tax thresholds. Our definition of policy changes is consistent with the decomposition literature (e.g. Bargain and Callan 2010 and Paulus et al. forthcoming). Automatic stabilisers capture the automatic changes to benefit entitlements and tax liabilities in response to changes in the distribution of gross market incomes and population characteristics, holding constant the tax-benefit rules.

In more detail, we construct counterfactual income distributions, which represent what would have happened to household incomes in the absence of changes to a certain factor – either to tax-benefit policies or to market incomes and population characteristics. Comparing the observed and counterfactual distributions allows us to quantify the contribution of each factor to the change in incomes. Our decomposition approach builds on and extends the method by Bargain and Callan (2010). We use the EU tax-benefit model EUROMOD to calculate actual and counterfactual entitlements to cash benefits and direct income taxes and social insurance contributions (SIC) for each household in the micro-data. The micro-data contain information on population characteristics and market incomes and come from the European Union Statistics on Income and Living Conditions (EU-SILC) and, for the UK, from the Family Resources Survey (FRS).

Between 2007 and 2014, market incomes became more unequally distributed in more than a third of countries. In the rest of countries, there was no statistically significant change in inequality as measured by the Gini coefficient. Our results show that, discretionary policy changes in 21 countries lowered inequality, consistent with the existing evidence. Our decomposition by tax-benefit policy adds to the evidence by showing that the reduction was achieved mainly through increased generosity of benefit entitlements, rather than through taxes/SIC. In some countries the impact of benefit changes was enhanced by inequality-reducing tax changes, while in others, benefit changes offset a rise in inequality due to tax changes (e.g. due to the introduction of a flat tax in Bulgaria and Hungary or the reduction in top marginal tax rates in Denmark). Among the countries implementing progressive policy changes overall were not only those where the welfare state expanded in size but also countries, which implemented fiscal consolidation measures in the economic downturn.

Automatic stabilisers also contributed in nearly half of the countries to lower inequality. Although discretionary policies were more often inequality-reducing, the magnitude of the two types of effect was broadly similar when it comes to narrowing the gap between the rich and the poor. A further decomposition of the automatic stabilisation effect shows that the effect of benefit stabilisation was to reduce inequality in most countries, whereas taxes/SIC had a mixed effect. The impact on net income of the stabilisation response of taxes/SIC was negatively associated with changes to market incomes/population characteristics across countries. However, there was effectively no country-level correlation between the stabilisation response of benefits and market income/population changes. This suggests that – unlike taxes/SIC – benefits are overall more responsive to changes in the population structure (such as household composition changes) than changes in market income.

The rest of the paper is structured as follows: Section 2.2 explains the decomposition methodology and provides our refinements and extensions to it. Section 2.3 describes the data and the tax-benefit model EUROMOD. Section 2.4 presents and discusses the results and Section 2.5 concludes.

2.2 Methodology

The central question of the paper is which factors contributed to household income changes in the EU countries between 2007 and 2014. In particular, we aim to disentangle the contribution of discretionary tax-benefit policy changes, automatic stabilisers and changes to market incomes and population characteristics. Section 2.2.1 presents and refines the decomposition approach formalised by Bargain and Callan (2010) – BC hereafter – which allows us to identify the direct effect of policy changes (i) from all 'other effects'. Section 2.2.2 extends the BC approach by splitting the 'other effects' into automatic stabilisers (ii) and changes to the distribution of market incomes and population characteristics (iii).

2.2.1 Decomposing discretionary policy changes vs other effects

We separate the direct effect of discretionary policy changes from all other factors by means of counterfactual simulations. Intuitively, we can think of it in this way: we start with the actual end-period income distribution (in 2014) and create intermediate counterfactual scenarios in which we change one factor of interest at a time, until we arrive at the actual start-period income distribution (in 2007). A comparison of the actual and counterfactual distributions unveils how much of the income change that is observed is due to policy changes and how much due to other effects. We use the decomposition approach by BC, which combines household micro-data with a tax-benefit calculator.[3] We refine the methodology by identifying a broader range of combinations and explicitly distinguishing between scale-variant and scale-invariant measures of the income distribution.

Following BC, denote with $I(\cdot)$ a functional of the distribution of household income, such as the Gini coefficient or mean income. Household net incomes in period t are expressed in the form of $d_t(p_t, y_t)$ of which: d is the structure of tax-benefit policies (e.g. means-tested vs universal child benefit), p are the tax-benefit parameters (e.g. €1,000 family income-test threshold), y is a matrix containing information on gross market incomes (e.g. earnings and investment income) and household/individual characteristics, and d transforms p and y into household net income. The change in the composite indicator I between two periods ($t = 0, 1$), calculated for the distribution of household net incomes, is given by

$$\Delta I = I[d_1(p_1, y_1)] - I[d_0(p_0, y_0)] \tag{2.1}$$

Next, we add and subtract an (intermediate) counterfactual distribution to separate the contribution of policy changes ($d_0, p_0 \rightarrow d_1, p_1$) from changes in market incomes and population characteristics ($y_0 \rightarrow y_1$). For example, such a counterfactual can be constructed using the tax-benefit structure and policy parameters from the start-period in combination with gross market incomes and population characteristics from the end-period, yielding the following identity:

$$\Delta I = \underbrace{I[d_1(p_1, y_1)] - I[d_0(p_0, y_1)]}_{\text{discretionary policy changes (nominal)}} + \underbrace{I[d_0(p_0, y_1)] - I[d_0(p_0, y_0)]}_{\text{other effects (nominal)}} \tag{2.2}$$

The difference between the actual distribution of the end-period ($t = 1$) and the counterfactual gives the direct effect due to *discretionary policy changes*. It gives an answer

[3] There is a well-established strand in the economic literature which focuses on decomposing the distribution of individual earnings, e.g. Juhn et al. (1993), DiNardo et al. (1996), Lemieux (2002), Fields (2003), Yun (2006), see Fortin et al. (2011) for an overview. However, this strand overlooks the role of taxation and ignores other income components. Bourguignon et al. (2008) take a step further by looking at household level income which includes market incomes, private transfers and retirement income but still excludes taxes and non-retirement benefits. The classical source decomposition of income inequality by Shorrocks (1982) accounts for all income components; but does not allow isolating the effects due to policy changes from effects due to market income changes, or decomposing incomes in nominal terms.

to the question: given the distribution of market incomes and population characteristics in $t = 1$, what would have been the impact on the income distribution if we were to re-introduce the tax-benefit policies from $t = 0$. If the answer is that the outcome of interest, e.g. income inequality, would have been higher (compared to the observed outcome in $t = 1$), it means that all else being equal, discretionary policy changes reduced the level of inequality. The difference between the counterfactual and the observed income distribution in the start-period ($t = 0$) unveils the contribution of the *other effect*, i.e. changes in market incomes and the characteristics of the population (e.g. employment) as well as the reaction to these of the tax-benefit policies from $t = 0$. The other effects also contain any changes to market incomes and population as a result of a behavioural response to the tax-benefit policy changes.[4]

In equation 2.2, tax-benefit policy amounts such as tax income thresholds or benefit amounts from the start-period (p_0) are applied on market incomes from the end-period (y_1). To make nominal amounts from the two periods comparable, policy parameters are in the next step adjusted by a factor α, which accounts for developments in nominal levels (e.g. prices, wages) or some other relevant counterfactual benchmark. Price indices appear most appropriate when the aim is to study how people's real living standards have changed, while changes in market incomes are more relevant for understanding shifts in the fiscal balance. In our analysis, we base α on growth in prices (Consumer Price Index):

$$\begin{aligned}\Delta I = \underbrace{I[d_1(p_1, y_1)] - I[d_0(\alpha p_0, y_1)]}_{\text{discretionary policy changes (real)}} + \underbrace{I[d_0(\alpha p_0, y_1)] - I[d_0(\alpha p_0, \alpha y_0)]}_{\text{other effect (real)}} \\ + \underbrace{I[d_0(\alpha p_0, \alpha y_0)] - I[d_0(p_0, y_0)]}_{\text{nominal effect}}\end{aligned} \tag{2.3}$$

As a result, in equation 2.3 there are two different counterfactuals that allow us to estimate in real terms the effect due to discretionary policy changes and other effects, as well as a pure scaling effect referred to as a *nominal effect*. For scale-invariant measures, such as the Gini coefficient, the nominal effect is zero as long as the tax-benefit system is

[4]Throughout the decomposition we are faced with an endogeneity problem: policy decisions may have been affected by the changes in the market and society and vice versa, the market and society may have been affected by policy changes. We do not estimate separately any behavioural responses to changes in the attributes, see Bargain (2012a) for estimating labour supply responses to the policy changes.

linearly homogeneous[5], which means that changing the nominal units of market incomes and tax-benefit policy parameters simultaneously would not affect the relative position of households in the income distribution.[6] For scale-variant measures of income, such as mean income, the nominal effect is non-zero as long as α is different from 1.[7]

The policy component captures both changes to the structure of the tax-benefit system as well as the effect of statutory uprating of/discretionary changes to monetary parameters, *relative* to α.[8] Thus, if tax-benefit parameters were only changed in line with CPI in practice, our analysis would consider the outcome neutral against our chosen benchmark indexation factor and the measured impact would be zero. If actual tax-benefit parameters were increased slower (faster) than prices, tax liabilities would go up (down) due to bracket creep and benefit entitlements would fall (rise) due to benefit erosion. See Paulus et al. (forthcoming) for more discussion on the choice of α and its implications for the measured policy effect.

Going back to equation 2.3, the decomposition is path-dependent, meaning that the order of decomposing the effects matters and there are alternative combinations. Building on BC, we derive six strictly symmetrical combinations (permutations) for three components, whereas they suggested four combinations because of their pairing of the other effect with the nominal effect.[9] Similar to BC, we distinguish between two types: Type I shows the effect of discretionary policy changes conditional on **end-period** market incomes and population characteristics (P_I) and the other effect conditional on ***start-period*** tax-

[5]That is, homogeneous of degree one: $d_0(\alpha p_0, \alpha y_0) = \alpha d_0(p_0, y_0)$.

[6]BC argue that tax-benefit systems are approximately linearly homogeneous, showing it explicitly for France and Ireland, and therefore omit the nominal effect as they focus on distributional measures rather than income changes explicitly.

[7]The nominal effect is approximately $(\alpha - 1)I[d_0(p_0, y0)]$ or $(\alpha - 1) \cdot 100\%$ in relative terms. Notice also that the *other effect* for decomposing changes in mean disposable income is approximately zero if $\alpha = \bar{y}_1/\bar{y}_0$, i.e. α is based on changes in average market income.

[8]To get a better understanding of government actions, Paulus et al. (forthcoming) extend the decomposition framework by distinguishing between the effect of changing the structure of the tax-benefit system (structural effect) from adjusting the tax and benefit monetary levels (indexation effect). Their analysis for 7 EU countries between 2001 and 2011 shows that overall, the indexation effect worked to reduce poverty and inequality in that period, stressing the importance of indexation of tax-benefit amounts in practice to avoid benefit erosion and fiscal drag. Structural reforms, on the other hand, worked in both ways – to reduce but also increase poverty and inequality.

[9]In principle, one could also consider first deflating I_1 (or inflating I_0) and then decomposing the real value of ΔI, as done e.g. in Herault and Azpitarte (2016), but this implies invoking the assumption of linear homogeneity from the very beginning. For example, denote an inflation factor with i and consider $d_1(p_1, y_1) - id_0(p_0, y_0) = d_1(p_1, y_1) - d_0(ip_0, iy_0) = [d_1(p_1, y_1) - d_0(ip_0, y_1)] + [d_0(ip_0, y_1) - d_0(ip_0, iy_0)]$, which is identical to eq. 2.3 but without the nominal effect (if $i = \alpha$). However, linear homogeneity is assumed already in the second step here, while it was not evoked (yet) in eq. 2.3.

benefit policies (O_I). Type II presents the effect of discretionary policy changes conditional on **start-period** market incomes/population (P_{II}) and the other effect conditional on ***end-period*** policies (O_{II}). Distinguishing between Type I and II has a clear practical relevance. While full decomposition can only be carried out once household micro-data become available for the whole period (which inevitably occurs with a time lag), Type II assessments for policy effects only require start-period household data and can be carried out before the policy changes have occurred, hence providing the basis for ex ante policy evaluation.

As there is no obvious reason to prefer a particular combination over the others, BC suggest following the Shorrocks-Shapley line of arguments. This essentially implies averaging the marginal contribution of decomposition terms across all combinations. We hence calculate the average effect due to discretionary policy changes, other and nominal effects using all six combinations, distinguishing between scale-variant and scale-invariant measures, defined as $I[\alpha d_t(p_t, y_t)] = \alpha I[d_t(p_t, y_t)]$ and $I[\alpha d_t(p_t, y_t)] = I[d_t(p_t, y_t)]$, respectively. In the following, the observed income distributions in $t = 0, 1$ (baselines) are denoted with $B_t = I[d_t(p_t, y_t)]$ and the counterfactuals as $C_t = I[d_{1-t}(p_{1-t}, \alpha^{1-2t} y_t)]$. Assuming linear homogeneity of the tax-benefit function $d(p, y)$, the average effect due to discretionary policy changes ($\overline{P}$), other ($\overline{O}$) and nominal ($\overline{N}$) effects, combining Type I and Type II decompositions for *scale-variant measures* are as follows:

$$\overline{P} = \frac{1}{2}[P_I + P_{II}] = \frac{1}{6}\left[\left(\frac{1}{\alpha} + 2\right)(B_1 - \alpha C_1) + (2 + \alpha)\left(\frac{1}{\alpha}C_0 - B_0\right)\right] \tag{2.4}$$

$$\overline{O} = \frac{1}{2}[O_I + O_{II}] = \frac{1}{6}\left[(2 + \alpha)(C_1 - B_0) + \left(\frac{1}{\alpha} + 2\right)(B_1 - C_0)\right] \tag{2.5}$$

$$\overline{N} = \frac{\alpha - 1}{6}\left[\frac{2}{\alpha}B_1 + 2B_0 + C_1 + \frac{1}{\alpha}C_0\right] \tag{2.6}$$

For *scale-invariant measures*, these expressions simplify further and the average effect due to discretionary policy changes ($\overline{P}$) and the average other effect ($\overline{O}$) (with the nominal effect ($\overline{N}$) being 0) are:

$$\overline{P} = \frac{1}{2}[P_I + P_{II}] = \frac{1}{2}[B_1 - C_1 + C_0 - B_0] \tag{2.7}$$

$$\overline{O} = \frac{1}{2}[O_I + O_{II}] = \frac{1}{2}\left[C_1 - B_0 + B_1 - C_0\right] \tag{2.8}$$

For details on the derivation of the effects, see Appendix 2.7.1.

We also split the impact on the income distribution of discretionary policy changes by benefits and taxes/SIC (estimating their joint distribution). Changes in mean income can be expressed simply as a sum of (simultaneous) changes to benefit entitlements and to tax/SIC liabilities, keeping gross market incomes fixed. For changes in income inequality (Gini coefficient), we quantify changes in the redistributive impact of benefits and taxes, keeping gross market incomes fixed. The redistributive impact of benefits is measured by calculating the difference between the Gini coefficients based on gross market income versus pre-tax income (gross market income + benefits). The redistributive impact of taxes/SIC is measured by calculating the difference between the Gini coefficients based on pre-tax income versus net income (pre-tax income – taxes/SIC).

2.2.2 Decomposing the other effects: market income/population effect vs automatic stabilisers

In addition to the direct effect of policy changes, tax-benefit policies can affect the income distribution through automatic stabilisers. They capture the extent to which changes (shocks) in the distribution of gross market income and population characteristics (e.g. changes to earnings, varying rate of returns to human and financial capital etc.) translate into changes in the distribution of disposable income. We extend the BC decomposition method by decomposing the *other effect* and separating out the changes in market incomes/population characteristics from the automatic stabilisation effect of policies.

To show the contribution of automatic stabilisers to the changes in the income distribution, first we need to distinguish between gross and net incomes. Similar to Figari et al. (2015), we define $d_t(p_t, y_t) = y_t + f(d_t, p_t, y_t)$ where f denotes net transfers (i.e. benefits less taxes). Using the term for the *other effect* from equation 2.3, we can rewrite it as $I[y_1 + f(d_0, \alpha p_0, y_1)] - I[\alpha y_0 + f(d_0, \alpha p_0, \alpha y_0)]$. The automatic stabilisation effect can then be derived as the difference between the *other effect* and the contribution of market income/population changes.

To distinguish between the contribution due to market income/population changes and automatic stabilisers, the measure I needs to be additively decomposable by income source (y and f). While this is a straightforward application to some indicators (e.g. mean income), it is not for all functionals of the income distribution such as the Gini coefficient.[10] Using the expression for the *other effect* from equation 2.3, we can rewrite it in general terms as $(I[y_1] + I[f(d_0, \alpha p_0, y_1)]) - (I[\alpha y_0] + I[f(d_0, \alpha p_0, \alpha y_0)]) + \epsilon$, where ϵ is a residual term. The value of the residual is zero for decomposing income changes but may be non-zero for decomposing other composite functions of income, which are not additively decomposable by income source. Hence, our decomposition of changes to mean incomes unveils the pure contribution of market income/population changes and automatic stabilisers. When we decompose changes in income inequality our decomposition shows the joint effect of the automatic stabilisers and the residual term.[11]

We denote as $B_t^* = I[y_t]$ the observed (baseline) distribution of gross market incomes and population characteristics in $t = 0, 1$ and as $C_t^* = I[\alpha^{1-2t} y_t]$ the counterfactual distribution. For *scale-variant* measures, the market income and population effect (M), averaged across all Type I and II combinations, equals:

$$\overline{M} = \frac{1}{2}[M_I + M_{II}] = \frac{1}{6}\left[(2+\alpha)(C_1^* - B_0^*) + \left(\frac{1}{\alpha} + 2\right)(B_1^* - C_0^*)\right] \tag{2.9}$$

The difference between the *other* and market income/population effects gives the effect of automatic stabilisers (A):

$$\begin{aligned} \overline{A} &= \frac{1}{2}[A_I + A_{II}] = \\ &= \frac{1}{6}\left[(2+\alpha)(C_1 - B_0 - (C_1^* - B_0^*)) + \left(\frac{1}{\alpha} + 2\right)(B_1 - C_0 - (B_1^* - C_0^*))\right] \end{aligned} \tag{2.10}$$

In equation 2.10, the tax-benefit rules and parameters are fixed either at t_0 (for A_I) or at t_1 (for A_{II}), while assessing the effect of changes in the distribution of gross market incomes and population characteristics. In other words, the effect of automatic stabilisers

[10] Some methods for decomposing inequality measures link the contribution of a given income source to overall income inequality with the inequality of the income source itself, its share in total income and/or correlation with total income (Shorrocks, 1982; Lerman and Yitzhaki, 1985; Silber, 1993).

[11] Callan et al. (2018) similarly separate the impact of automatic stabilisers on the Gini coefficient and have a residual term as well.

captures the automatic change in benefit entitlements and tax/SIC liability in response to the change in market incomes and population characteristics.

For *scale-invariant* measures, the average market income/population effect is

$$\overline{M} = \frac{1}{2}[M_I + M_{II}] = \frac{1}{2}\left[C_1^* - B_0^* + B_1^* - C_0^*\right] \tag{2.11}$$

and the effect due to automatic stabilisers is

$$\overline{A} = \frac{1}{2}[A_I + A_{II}] = \frac{1}{2}\left[C_1 - B_0 - (C_1^* - B_0^*) + B_1 - C_0 - (B_1^* - C_0^*)\right] \tag{2.12}$$

For details on the derivation of the effects, see Appendix 2.7.1.

Furthermore, we break down the change in mean incomes and in inequality due to automatic stabilisers by benefits and taxes/SIC. For changes in mean income, we estimate the automatic change to benefit entitlements and tax/SIC liabilities. As with discretionary policy changes, we make use of different income concepts to quantify their contribution to income inequality: gross market income, pre-tax income and net income.

Finally, standard errors are provided for the change in mean incomes based on Taylor approximations and for the change in income inequality measured by the Gini coefficient by bootstrapping the micro-data samples 1,000 times.

2.3 Data and the tax-benefit model EUROMOD

The household survey data come from the European Union Statistics on Income and Living Conditions (EU-SILC) and, for the UK, from the Family Resources Survey (FRS). Both surveys are purpose-built income surveys. For most countries, we use SILC waves for 2008 and 2015 (with income reference period 2007 and 2014) and for the UK FRS waves for 2008/09 and 2014/15 incomes, i.e. the most recent waves available. Due to data availability, income reference years are 2011 and 2014 for Croatia; 2007 and 2013 for Germany; 2008 and 2014 for Malta; and 2006 and 2014 for France. The data are cross-sectional and contain rich information on household and individual incomes and characteristics for a nationally representative sample of households. The data collection and production of EU-SILC in the EU member states have been made as consistent as possible to enable cross-country comparative analysis.

For baseline (counterfactual) simulations, we apply tax-benefit policies – structure and parameters – from one period to the household data on gross market incomes and population characteristics from the same (another) period. This is done by combining the household data with the EU-wide tax-benefit model EUROMOD. Using tax-benefit routines, EUROMOD contains information on the tax-benefit rules in a specific period for a given country. The model then reads the household survey data and based on the information in the data, it identifies who should pay an income tax/SIC or receive a benefit (e.g. the family or individual), and how much needs to be paid in taxes/contributions and received in benefit entitlements. The model then combines the information on gross market incomes from the household data with the calculated tax liabilities and cash benefit entitlements to derive household net incomes. Similar to the household data, EUROMOD simulations have been made as consistent as possible across all countries for the purpose of cross-country comparative research.

EUROMOD simulation results for each policy year included in the model are validated extensively against administrative data on benefit recipients/tax payers and benefit spending/tax revenues. Simulation routines (e.g. assumptions or limitations), data imputations and validation of the results are documented in detail in Country Reports made available online.[12] In addition, summary reports containing validation and discussion of EUROMOD baseline distributional statistics are published on an annual basis.[13] EUROMOD has been used extensively to address various economic and social policy research questions, see Sutherland and Figari (2013) and Figari et al. (2015) for literature reviews. In particular, the need for a comparative microsimulation model for decomposing changes in the income distribution has made EUROMOD an invaluable tool in the related literature.

We deal with cash household net incomes which comprise the sum of gross market incomes (earnings, self-employment income, investment income, income from rent and private transfers), pensions, means-tested and non-means-tested benefits net of personal income taxes and employee and self-employed SIC. Means-tested, universal and some con-

[12] https://www.euromod.ac.uk/using-euromod/country-reports

[13] For the latest issues, see Tammik (2018) and EUROMOD (2018). The latter report relies on a EUROMOD tool, which was developed as part of this paper.

tributory insurance-based benefits as well as direct income taxes and contributions are calculated by EUROMOD while information on the rest of incomes is taken from the household data. Although public pensions are not simulated (due to insufficient information on contributory history in the data), the policy change is approximated through the official indexation factor used by governments to adjust nominally pension amounts over time. In absence of large compositional changes in the population (the period we consider is relatively short), the indexation factor serves as a good proxy for the policy change. In our analysis of distributional changes, the remaining changes in pension amounts such as those due to changing pension age – not captured through indexation – is included in the component of 'market income/population effect'.

In cases where there is evidence for benefit non take-up or tax non-compliance, the simulation results are adjusted to account for it. Adjustments are done for benefit non-take-up in Belgium, Estonia, Finland, France, Greece, Ireland, Latvia, Poland, Portugal, Romania and the UK; and for tax non-compliance in Bulgaria, Greece, Italy and Romania (see Appendix 2.7.2).

The analysis is based on household equivalised incomes. Incomes are equivalised based on the assumptions that individuals share resources equally with other household members and economies of scale occur within the household. Incomes are adjusted by the modified OECD equivalence scale, assigning a value of 1 to the head, 0.5 for each other individual aged >=14 and 0.3 for each individual aged <14.

2.4 Results

2.4.1 Changes in mean incomes

The changes to net incomes between 2007 and 2014 are decomposed into the changes due to discretionary policies, automatic stabilisers, changes to gross market incomes and population characteristics as well as the nominal effect. Using the CPI-based benchmark indexation factor, the latter component reflects how prices developed and allows other components to be interpreted in real terms. In the first step, we present the combined effect of automatic stabilisers and changes to gross market incomes and population characteristics as in Bargain and Callan (2010), labelled 'other effect'. We then extend the standard decomposition approach by distinguishing between the two sub-components.

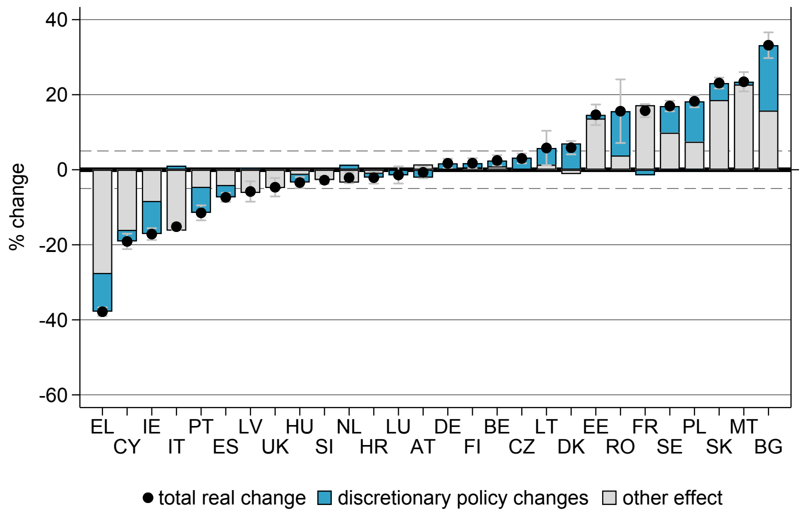
While average net incomes increased in nominal terms in the majority of countries, real incomes fell in half of countries and rose in the other half, with the change ranging from -37.8% (Greece) to +33.2% (Bulgaria). Figure 2.1 ranks countries by the real change in mean household net incomes (black circle); the nominal effect is not shown here as it corresponds closely to the CPI reported in Table 2.1.[14] Some of these changes are very substantial and it is remarkable that the extremes occurred in neighbouring countries. Among the countries experiencing a drop in real income were the ones hit badly by the crisis in the late 2000s such as Southern European countries, Ireland and Latvia, while the countries with the highest real income growth include some Eastern European countries as well as Malta, France and Sweden.

Similarly, countries are roughly split by whether changes in market incomes and population characteristics (here also including automatic stabilisers) and discretionary policy effects made a positive or negative contribution to household incomes on average. The two effects went in the same direction in almost all countries, in other words, discretionary policies largely reinforced market and population dynamics. The positive relationship between the two components at the country level suggests that in the cases where economic conditions were favourable – i.e. incomes growing due to 'other effects' – governments' tax-benefit policies boosted household disposable incomes as well. In contrast, countries experiencing economic contraction implemented fiscal consolidation measures, which squeezed further household budgets. Of course, such a positive correlation is expected at least in the long-term as governments ought to balance their budgets over the business cycle. We return to this point below.

Our results for discretionary policy changes are consistent with those by De Agostini et al. (2016). Focusing on policy changes only, they show further that Southern European countries implemented fiscal consolidation measures in both the crisis period (2008-11) as well as in the aftermath (2011-14), reinforcing the drop in mean incomes. On the other hand, they show that the large rise in incomes due to discretionary policy changes

[14] The sum of all components together with the nominal effect corresponds to the total nominal change in incomes.

Figure 2.1: Decomposing the change in mean net income: discretionary policy changes vs other effects

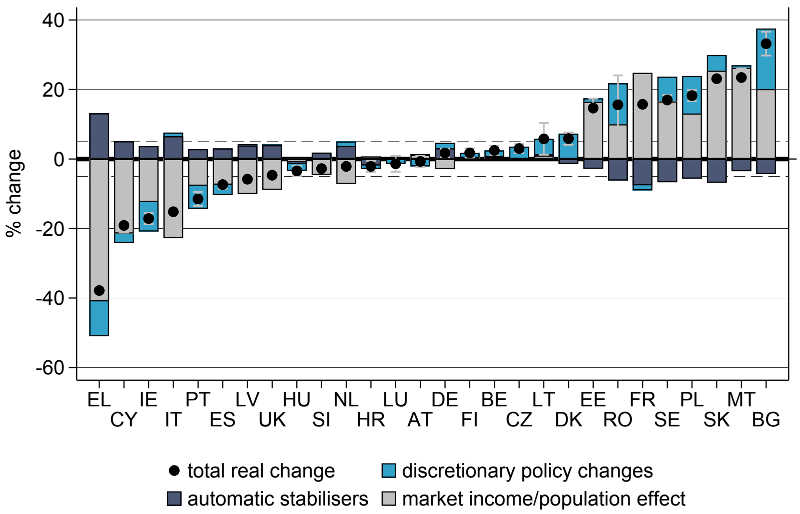


Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: Countries are ranked by the total real change in equivalised household net incomes. Income changes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

in Bulgaria, Sweden, Poland and Denmark was due to fiscal stimulus measures being implemented in both periods.

Next, to unveil the effect of automatic stabilisers, we apply our extension to BC method and decompose in Figure 2.2 the 'other effect' into the components due to changes in market incomes and population characteristics (grey bars) and automatic stabilisation response of policies (dark blue bars). Our decomposition clearly reveals that changes in average incomes in this period have been driven by market incomes and population changes. In progressive tax-benefit systems, such as the ones in EU countries, a shock to gross market incomes should be smoothed by fiscal policies. Confirming this, in all countries automatic stabilisers worked in the opposite direction to the market income/population effect. Thus, in countries where average gross market incomes fell, part of the negative shock was offset by automatic increases in benefit entitlements and reductions in tax liabilities and social insurance contributions (SIC); conversely, gains in gross market incomes were lowered through automatic reductions to benefits and increases in taxes/SIC. This can be seen more clearly in Figure 2.3, plotting automatic stabilisation effect and discretionary policy changes against market income and population effect. More than half of countries are situated in the left upper section of the left panel in Figure 2.3, highlighting the importance of the tax-benefit system to cushion the adverse income shocks households endured in the crisis. We estimate a correlation of -0.95 between the effect of automatic stabilisers and the market income/population effect across countries.

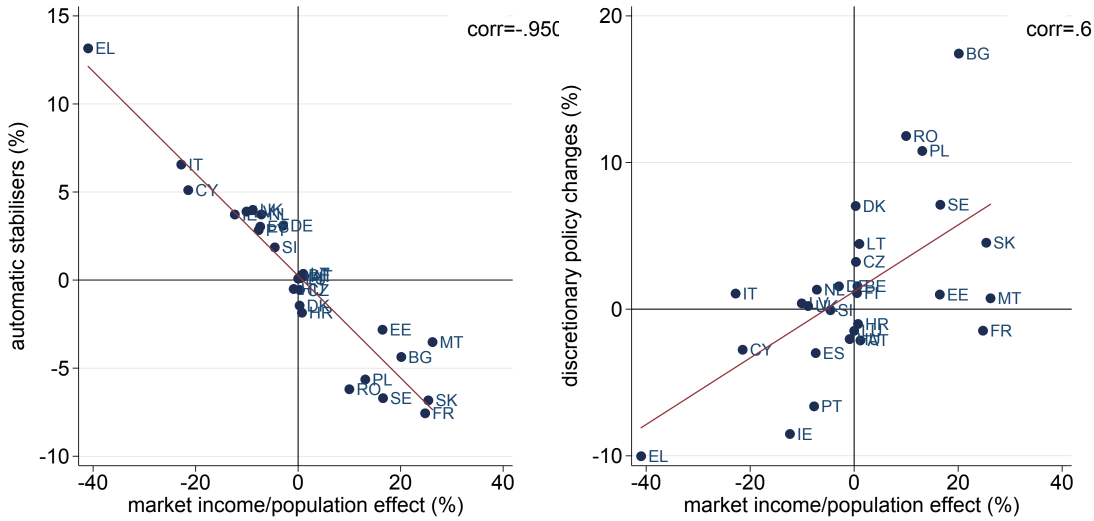
Figure 2.2: Decomposing the change in mean net income: discretionary policy changes vs automatic stabilisers



Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: Countries are ranked by the total real change in equivalised household net incomes. Income changes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

The correlation between discretionary policy changes and changes in gross market income and population characteristics is 0.59 (right panel of Figure 2.3). This reflects governments' resource constraints in broad terms (as already briefly discussed above). However, the result only relates to cash benefits and taxes/SIC affecting household disposable incomes directly. It is conceivable that governments may have counterbalanced these effects through other means, in particular, through adjusting spending on social protection in-kind and public services like health and education as well as changes to indirect taxation. To check that, we have plotted our measure of discretionary (cash) policy changes against these four items (Figure 2.9 in Appendix 2.7.3). We use Eurostat data available on total government spending on social protection in-kind, health and education and calculate changes in spending per capita between 2007 and 2014 in 2007 incomes (as a percentage of per capita disposable income estimated with EUROMOD). The effects of changes to indirect taxation are limited to changes in standard VAT rate, which we approximate by assuming that all income is spent on goods and services subject to the standard rate of VAT. We find that the correlation with all four items is positive (stronger in the case of spending measures), suggesting that across countries changes in these policy measures complemented rather than offset the effects of discretionary cash policies.

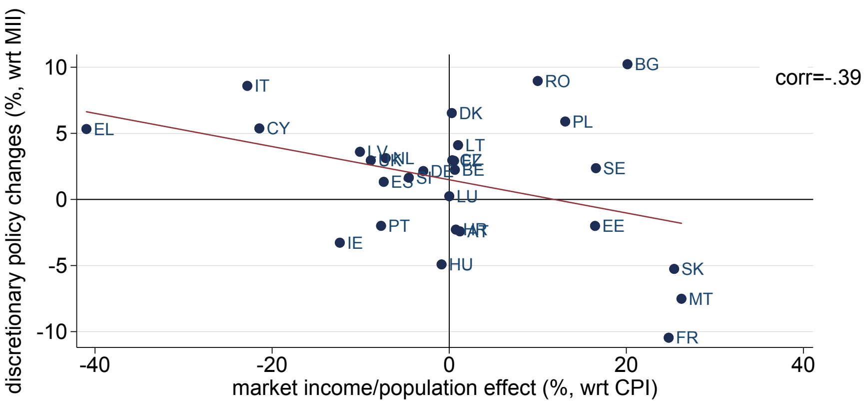
Figure 2.3: Correlation of automatic stabilisers and discretionary policy changes against the market income/population effect



Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: The vertical axis shows the % change in mean net income due to automatic stabilisers or discretionary policy changes. The horizontal axis shows the % change in mean net income due to the market income/population effect. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

As such, the positive correlation between discretionary policy changes and the market income/population effect (right panel of Figure 2.3) suggests that when the economy grows, governments have more financial resources at their disposal, through larger tax revenues, and so, they increase their spending overall. However, this result should not be interpreted as evidence for pro-cyclical policy changes, i.e. that the net public spending (benefit spending net of tax revenues) increases (decreases) faster than the economy grows (contracts). To understand how the structural balance of governments' finance varies with the business cycle, we need to measure the effect of policy changes viz-a-viz growth in the economy. We do this by estimating the policy effects *relative to* the growth in mean gross market incomes (labelled as Market Income Index or MII). For policy actions to be fiscally neutral towards household disposable incomes, the net contribution of benefits and taxes to household disposable incomes on average should remain constant over time (as a share of total income). A raising share of benefits would mean that policies have become more generous, while a declining share would reflect fiscal tightening. Figure 2.4 plots discretionary policy changes (assessed with MII) against changes in gross market incomes (assessed with CPI) – our proxy for economic growth excluding the effect of policy measures – revealing a weak negative correlation. This suggests that changes in fiscal balances due to direct taxes and cash benefits were, if anything, counter-cyclical.

Figure 2.4: Correlation of discretionary policy changes (assessed against MII-benchmark) against the market income/population effect (assessed against CPI-benchmark)

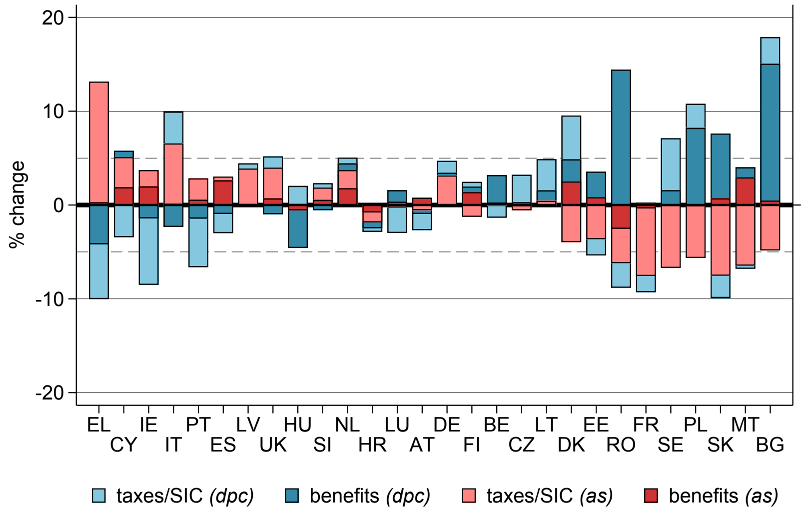


Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: The vertical axis shows the % change in mean net income due to discretionary policy changes. The horizontal axis shows the % change in mean net income due to the market income/population effect. Changes to incomes are estimated in real terms. Discretionary policy changes are assessed against MII (growth in average market incomes). The market income/population effect is assessed against CPI. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

2.4.2 Changes in mean incomes by policy instruments and income deciles

The impact on incomes due to discretionary policy changes and automatic stabilisers is further decomposed by benefits and taxes/SIC policies (Figure 2.5). It clearly shows that automatic responses were mainly realised through taxes and SIC and, on average, benefits played only a modest part. Furthermore, changes to net income due to taxes/SIC as automatic stabilisers were negatively associated with changes to market incomes/population characteristics (correlation of -0.96), while there was effectively no correlation between the stabilisation response of benefits and market income/population changes (-0.14) (Figure 2.10 in Appendix 2.7.3). This suggests that overall changes in benefits are driven by changes to population characteristics (such as household composition changes) rather than to market incomes. On the other hand, the composition of discretionary policy actions was more balanced and most of the income gains were due to benefits (Figure 2.5). Unlike with automatic stabilisers, the correlation between discretionary policy changes and market income/population effect was stronger in the case of benefits compared to taxes/SIC (cf. Figure 2.11 in Appendix 2.7.3). Detailed results on the decomposition of changes to mean incomes can be found in Table 2.2.

Figure 2.5: Decomposing the *change* in mean net income by type of policy



Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: dpc=discretionary policy changes; as=automatic stabilisers. The total change and market income/population effect are omitted. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

We also examine how similar are the impacts of fiscal policies and shocks to the economy on household incomes across the income distribution. We find that the patterns of total change in incomes varied greatly and were neither continuously progressive nor regressive in majority of cases (Figure 2.12 in Appendix 2.7.3). We repeat the decomposition by income decile and by country. The effect of discretionary policy changes was pro-poor in most countries, with Hungary and Denmark as the main exceptions (Figure 2.13 in Appendix 2.7.3). In these two countries, the richest decile groups benefited relatively more than households in the rest of the distribution through the introduction of a flat income tax (Hungary) and a reduction in tax rates (Denmark). Overall, changes to taxes and SIC had a mixed effect on the income distribution. On the other hand, policy changes to benefits tended to be pro-poor and resulted mainly in income gains across the distribution. There were exceptions where benefit cuts and/or deterioration in the real value of benefits led to income losses, mostly born by the poorer (in Croatia, Germany, Hungary, Ireland, Portugal and the UK). With the exception of Greece, the indexation of public pensions – generally higher than price inflation – was clearly pro-poor across countries, leading to larger relative income gains at the bottom than at the top of the distribution. In Greece, pension cuts led to larger income losses at the bottom and middle than the top of the distribution.

Benefits as automatic stabilisers responded to market income and population changes primarily at the bottom part of the distribution (Figure 2.14 in Appendix 2.7.3). This is not surprising as many benefits in EU countries are means-tested and are targeted by design at lower-income households. Insurance-based unemployment benefits are also designed to respond to losses in earnings and the latter could push individuals towards the bottom of the distribution. As in many countries households at the bottom saw their market incomes falling, benefits automatically cushioned part of the income loss making their contribution to income changes mostly progressive. Although the impact on the population-mean income of benefits was small in most countries, they contributed to substantial income gains among poorer households (e.g. of more than 5% for the bottom decile in Belgium, Bulgaria, Cyprus, Germany, Estonia, Greece, Finland, France, Lithuania, Latvia, Malta, Portugal and Slovakia). Nevertheless, across all decile groups we estimate a weak correlation between changes in gross market incomes and the stabilisation response of benefits.[15] This result supports our hypothesis that benefits are more responsive than taxes/SIC to changes in the population characteristics, which may not be fully visible in changes to market incomes. For instance, universal benefits would not provide any stabilisation towards income shocks per se but they could reduce income fluctuations which result from changes to household characteristics. An example is the entitlement to universal child benefits in the presence of a child in the household.

In the middle and top of the distribution, income taxes had the biggest stabilisation response, which was regressive in some and progressive in other countries. Where market incomes fell throughout most of the income distribution, the automatic stabilisation response was regressive as households from the middle/top benefited more than the bottom from the reductions in taxes (in Germany, Greece, Ireland, Italy, Latvia, the Netherlands, Portugal and the UK). In other countries, increases in gross market incomes at the top of the distribution were mitigated by increases in taxes, making their contribution progressive (in Bulgaria, Denmark, Estonia, Spain, France, Malta and Sweden) (Figure 2.14 in Appendix 2.7.3).

[15] Our estimates vary between 0 and -0.27 for all decile groups, apart from the fourth decile where the correlation is estimated at -0.49.

Across all decile groups, with the exception of the bottom one, market income and population changes were strongly and negatively correlated with the stabilisation response of income taxes.[16] As the income tax schedule – whether progressive or flat – includes a tax free allowance in all EU countries, households from the bottom decile group pay no or very little taxes as a share of their income.[17] Therefore, income taxes are less responsive to changes in market incomes at the bottom than middle or top of the distribution.

Similarly, we find that SIC as automatic stabilisers are less strongly correlated with changes in market incomes in the bottom decile (estimate of -0.43).[18] Furthermore, we estimate a weaker correlation (of -0.69) for the top decile group than for the preceding eight deciles, which can be due to a higher share of unearned private income and the presence of the upper limit on the contribution base in most countries. With the latter, if earnings are above the maximum threshold, SIC are levied on the maximum instead of actual earnings, making them non-responsive to changes in earnings in this income range. In the rest of the income distribution, the automatic response of SIC to market income changes was similar in relative terms as SIC are usually levied as a flat rate on earnings (Figure 2.14 in Appendix 2.7.3). The distributional changes are further summarised in the next section.

2.4.3 Changes in income inequality

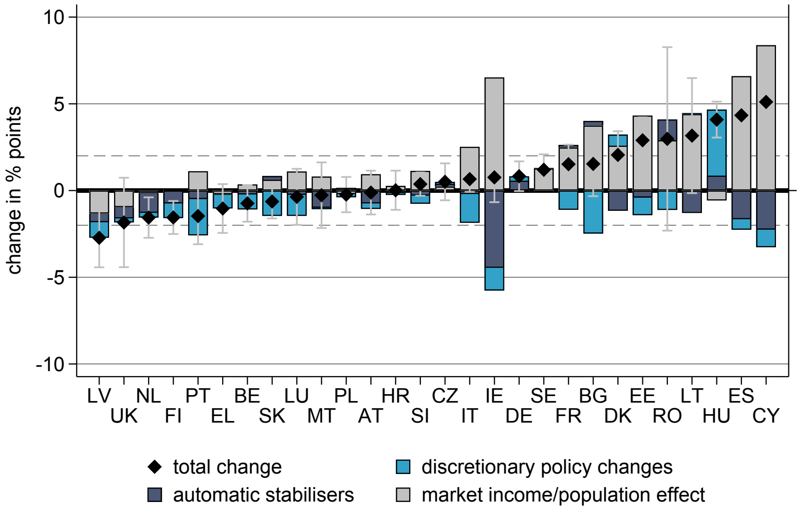
After studying changes along the income distribution, we turn to income inequality measured by the Gini coefficient. Figure 2.6 ranks the EU-28 countries by the inequality change between 2007 and 2014 and decomposes it into the same components as previously. Inequality changes ranged from -2.7 percentage points (Latvia) to +5.1 percentage points (Cyprus), increasing roughly in about half of the countries and decreasing in the rest, though the overall changes in inequality are relatively small and not statistically significant in many cases.

[16] Our estimate is -0.33 for the first decile group, -0.72 for the second and varies between -0.78 and -0.91 for the rest of the distribution.

[17] After the flat tax reform of 2008, only in Bulgaria individuals start paying income taxes from the first unit of income they earn. However, there are several tax deductions (e.g. for families with children) that act as a tax free allowance for certain household types. Furthermore, our decomposition results show the stabilisation response averaged over the 2007 and 2014 policies and thus they reflect the combined response of the progressive (2007) and flat (2014) tax schedule.

[18] For deciles 2-9, we estimate a correlation between -0.71 and -0.88.

Figure 2.6: Decomposing the *change* in Gini

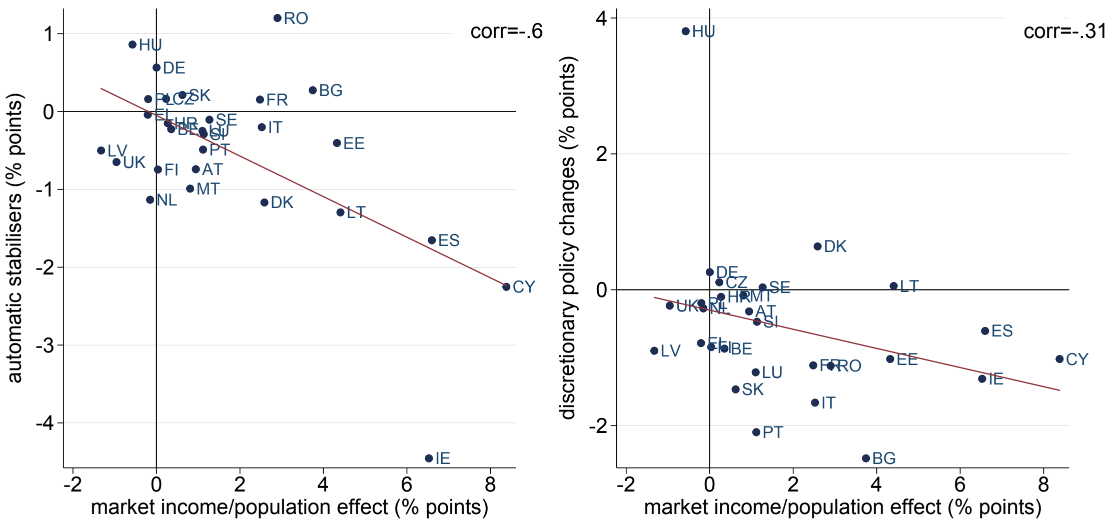


Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: Countries are ranked by the total change in Gini. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

However, the way different factors contributed to the total change in Gini was remarkably similar across countries. First, changes to the distribution of market incomes and population characteristics raised income inequality in nearly all countries (and were statistically significant in more than a third), with the change reaching 8.4 percentage points in Cyprus. Second, our results show that what helped to offset (part of) these increases was the tax-benefit system. Consistent with the previous literature on discretionary policy changes (e.g. Paulus et al., forthcoming; De Agostini et al., 2016; Bargain et al., 2017), we find that, albeit small in size, they lowered inequality in almost all countries. De Agostini et al. (2016) show that in most EU countries inequality fell due to discretionary policy changes in the crisis years (2008-11) as well as in its aftermath (2011-14). In addition, our results show that countries where inequality fell (Figure 2.6) were not only those where the welfare state expanded but also included those which implemented fiscal consolidation (Figure 2.2).

Moving to the effect of automatic stabilisers, we can establish that they had a statistically significant impact in about half of the countries, lowering inequality in most of them (Figure 2.6). We find a negative correlation between automatic stabilisers and the gross market income/population effect (see the left graph of Figure 2.7). However, this correlation is not as strong as with changes in mean incomes. This is expected as automatic stabilisers are foremost a tool for *income stabilisation* and not designed to directly react to changes in the *distribution* of incomes but income changes at the individual level. Hence, the sign of the relationship between automatic stabilisers and income inequality is ambiguous. In a few countries, the direction of inequality change due to automatic stabilisers was the same as for the change due to the market income/population effect (Latvia, UK, Slovakia, France, Bulgaria and Romania).[19]

Figure 2.7: Correlation of automatic stabilisers and discretionary policy changes against the market income/population effect



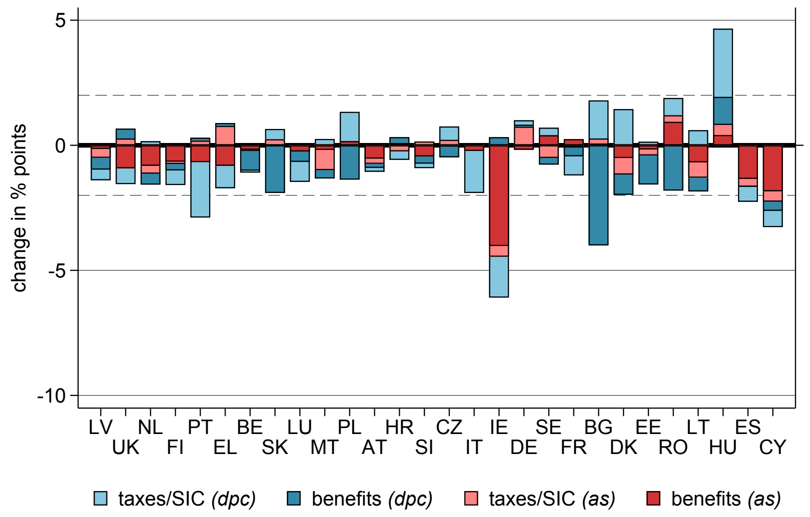
Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: The vertical axis shows the % points change in Gini due to automatic stabilisers or discretionary policy changes. The horizontal axis shows the % points change in Gini due to the market income/population effect. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Next, we break down discretionary policy changes and automatic stabilisers by benefits and taxes/SIC (Figure 2.8). We find that the inequality reduction due to policy changes was achieved mainly with benefits. In comparison, Callan et al. (2018) analysing the Southern EU countries (Greece, Italy, Portugal and Spain) and Ireland, find small or no changes to Gini due to benefit changes, which is also consistent with our results for these countries. In about a third of the EU countries, the inequality-reducing impact of benefit changes was enhanced by tax/SIC changes. In the remaining third, it offset the rise in inequality due to tax changes, e.g. due to the introduction of a flat tax in Bulgaria and Hungary or reduction in top marginal tax rates in Denmark. Moreover, in the countries

[19]It is also possible that compared to household net incomes, the effect of automatic stabilisers on inequality is measured less precisely due to the residual term discussed in Section 2.2.2. However, the fact that our main conclusions for changes to mean incomes and inequality are similar, suggests that the residuals have no critical role.

where benefit changes raised income inequality this was (at least partly) the result of erosion in the real value of benefits as their growth lagged behind growth in prices (e.g. in Germany, Hungary, Ireland and the UK).

Figure 2.8: Decomposing the *change* in Gini by type of policy



Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: dpc=discretionary policy changes; as=automatic stabilisers. The total change and market income/population effect are omitted. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

In their role as automatic stabilisers, benefits also reduced inequality in more countries than taxes/SIC did. They were the main stabilising source among the Southern EU countries and Ireland, consistent with the analysis by Callan et al. (2018) for these countries. At times when market incomes of the poor fall, means-tested benefits, at least partly, mitigate their losses. Increases in the unemployment rate, which are linked to an increase in the share of low-income households, triggers a similar response from insurance-based unemployment benefits. Such provision of pro-poor income stabilisation contributes towards narrowing the gap between the rich and the poor. However, it also means that when market incomes of the poor grow, benefit withdrawals would lower these gains, increasing the disparity between the bottom and the top of the distribution. How the response of benefits to changes in population characteristics impacts the income distribution is convoluted and depends on the type of population changes and where they occur along the distribution.

For income taxes, their distributional impact as automatic stabilisers generally depends on the size and direction of the income shock across the distribution, the progressivity of the tax schedule and the concentration of people across the tax schedule. Finally, the distributional impact of SIC as automatic stabilisers is more limited as in most countries a flat rate is applied on labour earnings.[20] Detailed results on the decomposition of changes to Gini can be found in Table 2.2.

2.5 Conclusions

Tax-benefit policies can affect the income distribution through two main channels: discretionary policy changes and automatic stabilisers. Although a large body of literature analyses the impact of tax-benefit policy changes on household incomes, little is known about the link between automatic stabilisers and the income distribution. We contribute to the literature by studying in detail the contribution of automatic stabilisers and discretionary policy changes to income changes in the EU countries between 2007 and 2014.

We find that, first, discretionary policy changes raised incomes on average in about two thirds of countries and lowered them in the remaining third. In comparison, on average automatic stabilisers – responding to changes to market incomes and population characteristics – led to income gains in about a third, losses in another third of countries and no statistically significant changes in the remaining third. In terms of income inequality, discretionary policy changes lowered it in more than two thirds of countries. Progressive policy changes were implemented not only in countries where the welfare state expanded in size but also in countries, which implemented fiscal consolidation measures in the economic downturn. Automatic stabilisers had a statistically significant impact on inequality in about half of countries, lowering inequality in most of them.

Second, discretionary policy changes to benefits – by increasing their level – and the automatic stabilisation response of benefits – mostly to income losses at the bottom of the distribution – were the main instruments raising the incomes of low-income households and narrowing the gap between rich and poor. Policy changes to and the automatic stabilisation response of taxes/SIC had a mixed effect on the income distribution of EU

[20] We estimate a weak and positive correlation of +0.1 between the impact of SIC as automatic stabilisers and the market income/population effect, on the Gini. In comparison, for the automatic stabilisation effect of taxes and benefits on the Gini, our estimates yield a correlation of -0.48 and -0.53, respectively, with the market income and population effect.

countries. While we find that changes in net income due to the stabilisation response of taxes/SIC were negatively associated with changes to market incomes and population characteristics, the correlation between the stabilisation response of benefits and market income/population changes was much weaker. This suggests that benefits are more responsive than taxes/SIC to changes in the population structure such as household composition changes.

Third, in terms of prevalence, discretionary policy changes lowered inequality in more countries than automatic stabilisers. But in terms of the size of the effects, we cannot conclude that policy changes contributed to inequality reduction more than automatic stabilisers, or vice versa. Thus, our findings show the importance of both discretionary policy changes and automatic stabilisers to redistribute incomes.

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2.6 Tables

Table 2.1: *Change (%) in prices (CPI) and market incomes (MII)*

	CPI	MII
AT	15.983	16.696
BE	15.376	13.954
BG	23.700	53.029
CY	14.548	-11.593
CZ	16.461	17.292
DE	10.726	9.174
DK	13.409	14.887
EE	29.263	43.178
EL	12.660	-33.578
ES	13.388	.658
FI	18.429	13.597
FR	13.407	39.665
HR	5.480	9.132
HU	29.035	36.329
IE	3.693	-8.655
IT	14.430	-5.299
LT	27.553	29.080
LU	16.957	12.783
LV	26.169	10.599
MT	11.902	42.110
NL	12.757	6.024
PL	21.037	39.144
PT	10.079	-1.830
RO	38.332	47.440
SE	10.562	24.279
SI	16.684	12.109
SK	15.608	46.576
UK	17.119	7.431

Notes: The value of the Consumer Price Index (CPI) is in fact equal to % change in prices based on the Harmonised Index of Consumer Prices. The value of the Market Incomes Index (MII) equals the growth in average unequivalised gross market incomes. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Source: For HICP, Eurostat database (indicator prc_hicp_aind). For MII, authors' calculations using EU-SILC and FRS data.

Table 2.2: *Decomposing the (%) change in mean household net income*

	total	mipe		discretionary policy changes					automatic stabilisers			
	change		benefits	pensions	taxes	SIC	total	benefits	taxes	SIC	total	
AT	-.705	1.425	-2.130***	.219	1.206	-.120***	-.281***	-1.185***	-.544***	.769***	-.682	.131
	(.8)	(.8)	(.0)	(.7)	(1.5)	(.0)	(.0)	(.0)	(.0)	(.2)	(.6)	(.2)
BE	2.471***	.906	1.565***	.270	.637	.354***	2.563***	-1.074***	-.279***	.154	.367	-.251
	(.7)	(.7)	(.0)	(.7)	(1.4)	(.0)	(.0)	(.0)	(.0)	(.1)	(.6)	(.2)
BG	33.188***	15.761***	17.427***	-4.366***	20.127***	2.295***	12.286***	3.370***	-.524***	.474***	-3.266***	-1.574***
	(1.7)	(1.6)	(.2)	(.5)	(2.1)	(.1)	(.2)	(.1)	(.0)	(.1)	(.3)	(.3)
CY	-19.106***	-16.339***	-2.767***	5.106***	-21.445***	-.357***	1.021***	-1.967***	-1.464***	1.890***	1.768***	1.448***
	(1.0)	(1.1)	(.1)	(.4)	(1.4)	(.0)	(.0)	(.0)	(.0)	(.1)	(.3)	(.1)
CZ	3.006***	-.220	3.226***	-.563	.343	-1.066***	1.366***	1.682***	1.244***	-.122	-.090	-.351*
	(.7)	(.7)	(.0)	(.4)	(1.0)	(.0)	(.0)	(.0)	(.0)	(.1)	(.2)	(.2)
DE	1.718**	.159	1.559***	3.088***	-2.929**	-.038*	.321***	.848***	.428***	-.060	2.236***	.913***
	(.6)	(.6)	(.0)	(.5)	(1.1)	(.0)	(.0)	(.0)	(.0)	(.1)	(.4)	(.2)
DK	5.876***	-1.159	7.035***	-1.447	.289	.914***	1.448***	4.734***	-.061***	2.506***	-4.020***	.067
	(.9)	(.9)	(.0)	(1.2)	(2.0)	(.0)	(.0)	(.0)	(.0)	(.4)	(1.0)	(.0)
EE	14.648***	13.650***	.997***	-2.818***	16.468***	.254***	2.474***	.004	-1.734***	.827***	-2.839***	-.806***
	(1.4)	(1.4)	(.0)	(.4)	(1.8)	(.0)	(.0)	(.0)	(.0)	(.1)	(.4)	(.1)
EL	-37.844***	-27.816***	-10.028***	13.155***	-40.971***	.767***	-4.956***	-4.903***	-.935***	.293***	7.300***	5.563***
	(.6)	(.6)	(.1)	(.3)	(.9)	(.0)	(.1)	(.0)	(.0)	(.1)	(.2)	(.1)
ES	-7.358***	-4.365***	-2.993***	3.033***	-7.399***	.020	-.969***	-1.966***	-.079***	2.627***	-.598*	1.004***
	(.6)	(.6)	(.0)	(.3)	(.9)	(.0)	(.0)	(.0)	(.0)	(.1)	(.2)	(.1)
FI	1.753**	.655	1.098***	.110	.546	.525***	.076***	2.054***	-1.556***	1.366***	-1.728***	.472***
	(.7)	(.7)	(.0)	(.5)	(1.1)	(.0)	(.0)	(.0)	(.0)	(.1)	(.3)	(.1)
FR	15.750***	17.219***	-1.469***	-7.563***	24.782***	.648***	-.381***	-1.236***	-.499***	-.366	-5.599***	-1.599***
	(.9)	(.9)	(.0)	(.7)	(1.5)	(.0)	(.0)	(.0)	(.0)	(.2)	(.4)	(.2)
HR	-2.115**	-1.104	-1.010***	-1.853***	.749	-.345***	-.273***	-.325***	-.068***	-.790***	-.235	-.829**
	(.8)	(.8)	(.0)	(.5)	(1.3)	(.0)	(.0)	(.0)	(.0)	(.2)	(.2)	(.3)
HU	-3.413***	-1.374	-2.039***	-.507	-.867	-4.660***	.642***	2.842***	-.863***	-.562***	-.021	.077
	(.8)	(.8)	(.1)	(.7)	(1.3)	(.1)	(.0)	(.1)	(.1)	(.2)	(.3)	(.4)
IE	-17.145***	-8.633***	-8.512***	3.723***	-12.355***	-1.798***	.373***	-6.617***	-.471***	1.980***	1.332*	.410***
	(.8)	(.8)	(.1)	(.8)	(1.6)	(.0)	(.0)	(.1)	(.0)	(.3)	(.6)	(.1)
IT	-15.179***	-16.241***	1.063***	6.561***	-22.803***	-.049***	-2.283***	3.808***	-.413***	.135***	4.935***	1.492***
	(.5)	(.5)	(.1)	(.3)	(.8)	(.0)	(.0)	(.1)	(.0)	(.0)	(.3)	(.1)
LT	5.802*	1.353	4.449***	.357	.997	-.105	1.228***	9.147***	-5.821***	-.083	.843	-.403
	(2.3)	(2.3)	(.1)	(.9)	(3.1)	(.1)	(.0)	(.2)	(.1)	(.3)	(.6)	(.2)
LU	-1.393	.086	-1.479***	.080	.006	.506***	.720***	-2.906***	.202***	.354	-.746	.472*

	(1.2)	(1.2)	(.0)	(.9)	(2.0)	(.0)	(.0)	(.0)	(.0)	(.2)	(.7)	(.2)
LV	-5.795***	-6.191***	.396***	3.889***	-10.080***	.248***	-.399***	2.320***	-1.773***	.079	2.296***	1.515***
	(1.4)	(1.4)	(.1)	(.5)	(1.8)	(.0)	(.0)	(.1)	(.0)	(.2)	(.4)	(.1)
MT	23.448***	22.706***	.743***	-3.520***	26.226***	.676***	.399***	.435***	-.768***	2.942***	-4.993***	-1.469***
	(1.3)	(1.3)	(.0)	(.7)	(1.9)	(.0)	(.0)	(.0)	(.0)	(.4)	(.5)	(.1)
NL	-2.123**	-3.451***	1.328***	3.725***	-7.176***	.565***	.141***	-.615***	1.237***	1.787***	2.734***	-.796***
	(.8)	(.7)	(.0)	(.6)	(1.3)	(.0)	(.0)	(.0)	(.0)	(.2)	(.4)	(.2)
PL	18.244***	7.454***	10.790***	-5.645***	13.099***	.442***	7.773***	-1.965***	4.541***	-.121*	-2.594***	-2.929***
	(.8)	(.8)	(.1)	(.4)	(1.2)	(.0)	(.1)	(.0)	(.0)	(.1)	(.3)	(.2)
PT	-11.489***	-4.862***	-6.627***	2.837***	-7.699***	-.308***	-1.134***	-4.902***	-.283***	.563***	.626	1.648***
	(1.0)	(1.0)	(.1)	(.6)	(1.6)	(.0)	(.0)	(.0)	(.0)	(.1)	(.5)	(.2)
RO	15.603***	3.795	11.807***	-6.198***	9.993*	1.364***	13.065***	-2.504***	-.117***	-2.536***	-1.829*	-1.833***
	(4.3)	(3.7)	(.7)	(1.1)	(4.8)	(.0)	(.8)	(.1)	(.0)	(.2)	(.8)	(.4)
SE	16.980***	9.862***	7.117***	-6.703***	16.566***	.184***	1.395***	5.693***	-.155***	-.104	-6.243***	-.356***
	(.7)	(.7)	(.0)	(.6)	(1.2)	(.0)	(.0)	(.0)	(.0)	(.1)	(.5)	(.1)
SI	-2.774***	-2.703***	-.071**	1.857***	-4.560***	.202***	-.739***	.907***	-.441***	.536***	.466*	.856***
	(.5)	(.5)	(.0)	(.4)	(.9)	(.0)	(.0)	(.0)	(.0)	(.1)	(.2)	(.2)
SK	23.103***	18.573***	4.530***	-6.828***	25.401***	1.591***	5.318***	1.021***	-3.400***	.708***	-3.073***	-4.463***
	(.7)	(.7)	(.1)	(.4)	(1.1)	(.0)	(.1)	(.0)	(.1)	(.1)	(.2)	(.2)
UK	-4.658***	-4.873***	.215**	3.986***	-8.859***	-1.396***	.415***	1.273***	-.077***	.698***	2.737**	.550***
	(1.3)	(1.2)	(.1)	(.9)	(2.1)	(.0)	(.0)	(.1)	(.0)	(.1)	(.9)	(.1)

Notes: mipe=market income/population effect. Standard errors are calculated based on Taylor approximations. Significance levels indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Source: Own calculations with EUROMOD and EU-SILC/FRS.

Table 2.2: *Decomposing the (% points) change in the Gini coefficient*

	total	mipe	discretionary policy changes			automatic stabilisers		
	change		benefits	taxes & SIC	total	benefits	taxes & SIC	total
AT	-.117	.943	-.163***	-.156***	-.319***	-.533*	-.208	-.742*
	(.6)	(.9)	(.0)	(.0)	(.0)	(.2)	(.2)	(.3)
BE	-.739	.354	-.787***	-.080***	-.867***	-.177	-.050	-.227
	(.5)	(.7)	(.0)	(.0)	(.0)	(.1)	(.2)	(.2)
BG	1.535	3.744***	-4.004***	1.523***	-2.481***	.073	.200	.273
	(.9)	(1.0)	(.1)	(.0)	(.1)	(.1)	(.1)	(.2)
CY	5.110***	8.382***	-.368***	-.651***	-1.019***	-1.837***	-.416	-2.253***
	(1.1)	(1.3)	(.1)	(.0)	(.1)	(.2)	(.3)	(.3)
CZ	.503	.231	-.426***	.536***	.110**	-.055	.218	.163
	(.5)	(.7)	(.0)	(.0)	(.0)	(.2)	(.1)	(.2)
DE	.826	.003	.077***	.182***	.259***	-.179	.743***	.564*
	(.4)	(.6)	(.0)	(.0)	(.0)	(.2)	(.1)	(.2)
DK	2.056**	2.586*	-.811***	1.449***	.638***	-.510	-.658**	-1.168*
	(.7)	(1.0)	(.0)	(.0)	(.0)	(.4)	(.2)	(.5)
EE	2.899***	4.323***	-1.164***	.145***	-1.019***	-.169	-.236**	-.405**
	(.7)	(.7)	(.0)	(.0)	(.0)	(.1)	(.1)	(.1)
EL	-1.035	-.208	.114*	-.900***	-.785***	-.817***	.775***	-.042
	(.7)	(.8)	(.0)	(.1)	(.1)	(.1)	(.1)	(.2)
ES	4.337***	6.597***	-.004	-.603***	-.606***	-1.342***	-.312**	-1.654***
	(.4)	(.5)	(.0)	(.0)	(.0)	(.1)	(.1)	(.2)
FI	-1.554**	.036	-.258***	-.586***	-.844***	-.656***	-.090	-.746***
	(.5)	(.5)	(.0)	(.0)	(.0)	(.2)	(.1)	(.2)
FR	1.520**	2.480**	-.347***	-.766***	-1.113***	.246	-.093	.153
	(.6)	(.8)	(.0)	(.0)	(.0)	(.2)	(.2)	(.3)
HR	.016	.273	.235***	-.340***	-.105***	.092	-.243	-.151
	(.6)	(.8)	(.0)	(.0)	(.0)	(.3)	(.2)	(.3)
HU	4.090***	-.575	1.077***	2.728***	3.805***	.412*	.448	.860*
	(.5)	(.7)	(.1)	(.1)	(.1)	(.2)	(.3)	(.4)
IE	.760	6.526***	.324***	-1.634***	-1.310***	-4.028***	-.428	-4.456***
	(.7)	(1.1)	(.0)	(.0)	(.1)	(.6)	(.3)	(.7)
IT	.660	2.523***	.022	-1.683***	-1.662***	-.224***	.023	-.202
	(.4)	(.4)	(.0)	(.1)	(.1)	(.0)	(.1)	(.1)
LT	3.167	4.408*	-.550***	.605***	.055	-.682**	-.614***	-1.296***
	(1.7)	(1.7)	(.1)	(.0)	(.1)	(.2)	(.2)	(.3)
LU	-.363	1.101	-.415***	-.800***	-1.215***	-.247	-.003	-.250
	(.8)	(1.1)	(.0)	(.0)	(.0)	(.3)	(.2)	(.4)
LV	-2.724**	-1.325	-.472***	-.426***	-.898***	-.146	-.355*	-.501*
	(.9)	(.9)	(.0)	(.0)	(.0)	(.1)	(.1)	(.2)
MT	-.269	.807	-.338***	.253***	-.085	-.185	-.806***	-.991
	(1.0)	(1.2)	(.0)	(.0)	(.0)	(.4)	(.2)	(.5)
NL	-1.559**	-.151	-.441***	.166***	-.274***	-.819***	-.315	-1.134***
	(.6)	(.7)	(.0)	(.0)	(.0)	(.2)	(.2)	(.3)
PL	-.235	-.197	-1.369***	1.173***	-.197***	.166**	-.007	.160
	(.5)	(.6)	(.0)	(.0)	(.0)	(.1)	(.1)	(.1)
PT	-1.471	1.116	.117**	-2.214***	-2.097***	-.675***	.185	-.490
	(.8)	(1.0)	(.0)	(.0)	(.1)	(.2)	(.2)	(.3)
RO	2.979	2.898	-1.813***	.692***	-1.121***	.939***	.262	1.201***
	(2.7)	(2.3)	(.3)	(.0)	(.3)	(.2)	(.2)	(.3)
SE	1.198**	1.269*	-.269***	.305***	.035	.400**	-.506**	-.106
	(.5)	(.6)	(.0)	(.0)	(.0)	(.1)	(.2)	(.3)
SI	.371	1.133*	-.292***	-.179***	-.471***	-.444***	.153	-.291
	(.3)	(.5)	(.0)	(.0)	(.0)	(.1)	(.2)	(.2)
SK	-.632	.622	-1.879***	.413***	-1.466***	-.029	.240	.212
	(.5)	(.7)	(.0)	(.1)	(.1)	(.2)	(.2)	(.2)
UK	-1.840	-.956	.397***	-.631***	-.234***	-.922***	.272	-.650*
	(1.3)	(1.5)	(.0)	(.1)	(.1)	(.2)	(.3)	(.3)

Notes: mipe=market income/population effect. Bootstrapped standard errors after 1,000 replications. Significance levels indicated as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Source: Own calculations with EUROMOD and EU-SILC/FRS.

2.7 Appendix

2.7.1 Type I and Type II decompositions

Type I

Under *Type I* decomposition, the effect due to discretionary policy changes is derived based on gross market incomes from end-period (y_1) while the other effect is based on policies from start-period (d_0, p_0). In addition to equation 2.3 (decomposing discretionary policy changes, other and nominal effects in that order) which falls under *Type I*, due to symmetry the total change in I can be also decomposed in this order: discretionary policy changes, nominal effect, other effect (equation 2.13) as well as nominal effect, discretionary policy changes, other effect (equation 2.14):

$$\begin{aligned}\Delta I = &\underbrace{I[d_1(p_1, y_1)] - I[d_0(\alpha p_0, y_1)]}_{\text{discretionary policy changes}} + \underbrace{I[d_0(\alpha p_0, y_1)] - I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right]}_{\text{nominal effect}} \\ &+ \underbrace{I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right] - I[d_0(p_0, y_0)]}_{\text{other effect}}\end{aligned} \tag{2.13}$$

$$\begin{aligned}\Delta I = &\underbrace{I[d_1(p_1, y_1)] - I\left[d_1\left(\frac{1}{\alpha}p_1, \frac{1}{\alpha}y_1\right)\right]}_{\text{nominal effect}} + \underbrace{I\left[d_1\left(\frac{1}{\alpha}p_1, \frac{1}{\alpha}y_1\right)\right] - I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right]}_{\text{discretionary policy changes}} \\ &+ \underbrace{I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right] - I[d_0(p_0, y_0)]}_{\text{other effect}}\end{aligned} \tag{2.14}$$

Following on this, we can derive the effect due to discretionary policy changes, other and nominal effects averaged over equations 2.3, 2.13 and 2.14. Thus, the average effect of discretionary policy changes conditional on end-period gross market incomes is:

$$\frac{2}{3}\left[I[d_1(p_1, y_1)] - I\left[\alpha d_0(p_0, \frac{1}{\alpha}y_1)\right]\right] + \frac{1}{3}\left[I\left[\frac{1}{\alpha}d_1(p_1, y_1)\right] - I\left[d_0(p_0, \frac{1}{\alpha}y_1)\right]\right] \tag{2.15}$$

The other effect conditional on start-period policies becomes:

$$\frac{1}{3}\left[I\left[\alpha d_0(p_0,\frac{1}{\alpha}y_1)\right]-I[\alpha d_0(p_0,y_0)]\right]+\frac{2}{3}\left[I\left[d_0\left(p_0,\frac{1}{\alpha}y_1\right)\right]-I[d_0(p_0,y_0)]\right] \tag{2.16}$$

Finally, the nominal effect is:

$$\begin{aligned}\frac{1}{3}\left[I\left[\alpha d_0(p_0,y_0)\right]-I[d_0(p_0,y_0)]\right]+\frac{1}{3}\left[I\left[\alpha d_0\left(p_0,\frac{1}{\alpha}y_1\right)\right]-I\left[d_0\left(p_0,\frac{1}{\alpha}y_1\right)\right]\right]\\ +\frac{1}{3}\left[I\left[d_1(p_1,y_1)\right]-I\left[\frac{1}{\alpha}d_1(p_1,y_1)\right]\right]\end{aligned} \tag{2.17}$$

Type II

Under *Type II* decomposition, the effect of discretionary policy changes is conditional on gross market incomes from start-period (y_0) while the other effect is conditional on policies from end-period (d_1, p_1). Under *Type II* decomposition (as with Type I) there are three ways to decompose the total change: nominal effect, other effect, discretionary policy changes (equation 2.18); other effect, nominal effect, discretionary policy changes (equation 2.19); and other effect, discretionary policy changes, nominal effects (equation 2.20):[21]

$$\begin{aligned}\Delta I=\underbrace{I[d_1(p_1,y_1)]-I\left[d_1\left(\frac{1}{\alpha}p_1,\frac{1}{\alpha}y_1\right)\right]}_{\text{nominal effect}}+\underbrace{I\left[d_1\left(\frac{1}{\alpha}p_1,\frac{1}{\alpha}y_1\right)\right]-I\left[d_1\left(\frac{1}{\alpha}p_1,y_0\right)\right]}_{\text{other effect}}\\ +\underbrace{I\left[d_1\left(\frac{1}{\alpha}p_1,y_0\right)\right]-I[d_0(p_0,y_0)]}_{\text{discretionary policy changes}}\end{aligned} \tag{2.18}$$

[21]A special Policy Effects Tool was developed in the tax-benefit model EUROMOD that generates all counterfactual permutations and allows the estimation of discretionary policy changes and other effects on the income distribution. At the time of writing, a simplified version of the tool is publicly available for research and policy uses.

$$
\begin{aligned}
\Delta I = \underbrace{I[d_1(p_1, y_1)] - I\left[d_1(p_1, \alpha y_0)\right]}_{\text{other effect}} + \underbrace{I[d_1(p_1, \alpha y_0)] - I\left[d_1\left(\frac{1}{\alpha}p_1, y_0\right)\right]}_{\text{nominal effect}} \\
+ \underbrace{I\left[d_1\left(\frac{1}{\alpha}p_1, y_0\right)\right] - I[d_0(p_0, y_0)]}_{\text{discretionary policy changes}}
\end{aligned}
\tag{2.19}
$$

$$
\begin{aligned}
\Delta I = \underbrace{I[d_1(p_1, y_1)] - I[d_1(p_1, \alpha y_0)]}_{\text{other effect}} + \underbrace{I[d_1(p_1, \alpha y_0)] - I[d_1(\alpha p_0, \alpha y_0)]}_{\text{discretionary policy changes}} \\
+ \underbrace{I[d_1(\alpha p_0, \alpha y_0)] - I[d_0(p_0, y_0)]}_{\text{nominal effect}}
\end{aligned}
\tag{2.20}
$$

To derive the average effect of discretionary policy changes, other and nominal effects for *Type II* decomposition, we take the arithmetic average over equations 2.18–2.20. As a result, the average effect of discretionary policy changes conditional on start-period gross market incomes becomes:

$$
\frac{2}{3}\left[I\left[\frac{1}{\alpha}d_1(p_1, \alpha y_0)\right] - I\left[d_0(p_0, y_0)\right]\right] + \frac{1}{3}\left[I\left[d_1(p_1, \alpha y_0)\right] - I\left[\alpha d_0(p_0, y_0)\right]\right] \tag{2.21}
$$

The average other effect conditional on end-period policies equals:

$$
\frac{1}{3}\left[I\left[\frac{1}{\alpha}d_1(p_1, y_1)\right] - I\left[\frac{1}{\alpha}d_1(p_1, \alpha y_0)\right]\right] + \frac{2}{3}\left[I\left[d_1\left(p_1, y_1\right)\right] - I[d_1(p_1, \alpha y_0)]\right] \tag{2.22}
$$

Finally, the average nominal effect is:

$$
\begin{aligned}
\frac{1}{3}\left[I\left[d_1(p_1, y_1)\right] - I\left[\frac{1}{\alpha}d_1(p_1, y_1)\right]\right] + \frac{1}{3}\left[I\left[d_1\left(p_1, \alpha y_0\right)\right] - I\left[\frac{1}{\alpha}d_1\left(p_1, \alpha y_0\right)\right]\right] \\
+\frac{1}{3}\left[I\left[\alpha d_0(p_0, y_0)\right] - I[d_0(p_0, y_0)]\right]
\end{aligned}
\tag{2.23}
$$

Average effects for scale-variant and scale-invariant measures

In this subsection, we use the linear homogeneity property to derive the average effect of discretionary policy changes, other and nominal effects as well as the effect of automatic stabilisers and market income/population effects. We do this first for ***scale-variant*** and then for ***scale-invariant*** measures.

Scale-variant measures

The baselines (the observed) income distributions in $t = 0, 1$ are denoted with $B_t = I[d_t(p_t, y_t)]$; the counterfactuals are denoted with $C_t = I[d_{1-t}(p_{1-t}, \alpha^{1-2t} y_t)]$. Beginning with scale-variant measures, for *Type I* decomposition, we can simplify equation 2.15 to present the average effect of discretionary policy changes conditional on end-period gross market incomes as:

$$P_I = \frac{1}{3}\left(\frac{1}{\alpha} + 2\right) I[d_1(p_1, y_1)] - (2\alpha + 1) I\left[d_0\left(p_0, \frac{1}{\alpha} y_1\right)\right] = \frac{1}{3}\left(\frac{1}{\alpha} + 2\right)(B_1 - \alpha C_1) \tag{2.24}$$

Similarly, equation 2.16 can be simplified to show the average other effects conditional on start-period policies as:

$$O_I = \frac{2+\alpha}{3}\left(I\left[d_0\left(p_0, \frac{1}{\alpha} y_1\right)\right] - I\left[d_0\left(p_0, y_0\right)\right]\right) = \frac{2+\alpha}{3}(C_1 - B_0) \tag{2.25}$$

Simplifying equation 2.17 gives the average nominal effect:

$$N_I = \left(\frac{\alpha - 1}{3}\right)\left(B_0 + C_1 + \frac{1}{\alpha} B_1\right) \tag{2.26}$$

Let us denote as $B_t^* = I[y_t]$ the baseline (the observed) distribution of gross market incomes and population characteristics in $t = 0, 1$ and as $C_t^* = I[\alpha^{1-2t} y_t]$ the counterfactual distribution of gross incomes. We can then present the effect of automatic stabilisers as the difference between the other effects and the market income/population effect. The market income/population effect is:

$$M_I = \frac{2+\alpha}{3}\left(I\left[\frac{1}{\alpha} y_1\right] - I\left[y_0\right]\right) = \frac{2+\alpha}{3}(C_1^* - B_0^*) \tag{2.27}$$

Thus, the effect of automatic stabilisers equals:

$$\begin{aligned} A_I = \frac{2+\alpha}{3}\left(I\left[d_0\left(p_0, \frac{1}{\alpha} y_1\right)\right] - I\left[d_0\left(p_0, y_0\right)\right] - \left(I\left[\frac{1}{\alpha} y_1\right] - I\left[y_0\right]\right)\right) = \\ = \frac{2+\alpha}{3}(C_1 - B_0 - (C_1^* - B_0^*)) \end{aligned} \tag{2.28}$$

For *Type II* decomposition, the average effect of discretionary policy changes conditional on start-period gross market incomes becomes based on equation 2.21:

$$P_{II} = \frac{1}{3}\left(\frac{2}{\alpha}+1\right) I[d_1(p_1,\alpha y_0)] - (2\alpha+1) I\left[d_0\left(p_0, y_0\right)\right] = \frac{2+\alpha}{3}\left(\frac{1}{\alpha}C_0 - B_0\right) \quad (2.29)$$

Simplifying equation 2.22 shows the average other effect conditional on end-period policies as:

$$O_{II} = \frac{1}{3}\left(\frac{1}{\alpha}+2\right)\left(I\left[d_1\left(p_1, y_1\right)\right] - I\left[d_1\left(p_1, \alpha y_0\right)\right]\right) = \frac{1}{3}\left(\frac{1}{\alpha}+2\right)\left(B_1 - C_0\right) \quad (2.30)$$

By simplifying equation 2.23, the average nominal effect becomes:

$$N_{II} = \left(\frac{\alpha-1}{3}\right)\left(\frac{1}{\alpha}B_1 + \frac{1}{\alpha}C_0 + B_0\right) \quad (2.31)$$

Decomposing the other effects into the market income/population and automatic stabilisation effects yields the following identities:

$$M_{II} = \frac{2+\alpha}{3}\left(I\left[\frac{1}{\alpha}y_1\right] - I\left[y_0\right]\right) = \frac{2+\alpha}{3}(C_1^* - B_0^*) \quad (2.32)$$

$$\begin{aligned} A_{II} = \frac{1}{3}\left(\frac{1}{\alpha}+2\right)\left(I\left[d_1\left(p_1, y_1\right)\right] - I\left[d_1\left(p_1, \alpha y_0\right)\right] - \left(I\left[y_1\right] - I\left[\alpha y_0\right]\right)\right) = \\ \frac{1}{3}\left(\frac{1}{\alpha}+2\right)\left(B_1 - C_0 - \left(B_1^* - C_0^*\right)\right) \end{aligned} \quad (2.33)$$

Scale-invariant measures

For scale-invariant measures, the nominal effect is zero. The average effect of discretionary policy changes, other effect, market income/population effect and effect of automatic stabilisers – first for *Type I* and then *Type II* decomposition – can be presented as follows:

$$P_I = I[d_1(p_1, y_1)] - I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right] = B_1 - C_1 \quad (2.34)$$

$$O_I = I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right] - I\left[d_0\left(p_0, y_0\right)\right] = C_1 - B_0 \quad (2.35)$$

$$M_I = I\left[\frac{1}{\alpha}y_1\right] - I\left[y_0\right] = C_1^* - B_0^* \quad (2.36)$$

$$A_I = I\left[d_0\left(p_0, \frac{1}{\alpha}y_1\right)\right] - I\left[d_0\left(p_0, y_0\right)\right] - \left(I\left[\frac{1}{\alpha}y_1\right] - I\left[y_0\right]\right) = C_1 - B_0 - \left(C_1^* - B_0^*\right) \tag{2.37}$$

$$P_{II} = I[d_1(p_1, \alpha y_0)] - I\left[d_0\left(p_0, y_0\right)\right] = C_0 - B_0 \tag{2.38}$$

$$O_{II} = I\left[d_1\left(p_1, y_1\right)\right] - I\left[d_1\left(p_1, \alpha y_0\right)\right] = B_1 - C_0 \tag{2.39}$$

$$M_{II} = I\left[y_1\right] - I\left[\alpha y_0\right] = B_1^* - C_0^* \tag{2.40}$$

$$A_{II} = I\left[d_1\left(p_1, y_1\right)\right] - I\left[d_1\left(p_1, \alpha y_0\right)\right] - \left(I\left[y_1\right] - I\left[\alpha y_0\right]\right) = B_1 - C_0 - \left(B_1^* - C_0^*\right) \tag{2.41}$$

2.7.2 Adjustments for benefit non-take-up and tax non-compliance in EUROMOD

Benefit non-take-up

Benefit non-take-up can have important implications for the income distribution. Benefits need to be claimed to reach the intended population and to mitigate income fluctuations that households experience. Due to incomplete take-up, reforms to benefits cannot achieve their intended impact on the income distribution either. Assuming full take-up, the number of benefit recipients would be overstated and the effect of policy changes to and the stabilisation response of benefits overestimated. To account for partial take-up, adjustments have been made in EUROMOD to the simulation of some benefits, for which there is (suggestive) evidence for incomplete take-up. Such adjustments are done in Belgium, Estonia, Finland, France, Ireland, Greece, Latvia, Poland, Portugal, Romania and the UK for the baseline simulations and maintained in our counterfactual simulations as well.

More specifically, fixed take-up probabilities are applied randomly on the sample of individuals/households simulated by EUROMOD to be eligible for means-tested benefits in: Belgium (income support), France (solidarity labour income), Greece (unemployment assistance, social dividend, food stamps and rent allowance), Ireland (family income supplement), Portugal (social solidarity supplement for the elderly) and the UK (housing benefit, council tax benefit, pension credit, income support, child and working tax credits). Take-up probabilities for specific benefits are applied at the household level, so that individuals within a given household, who are eligible for the same benefit, have the same take-up behaviour.

For Belgium, France, Greece and Portugal, take-up rates are estimated based on the ratio between the number of benefit recipients reported by official statistics and the number of eligible cases according to EUROMOD simulations. In Ireland, the take-up rate is based on external estimates. In the UK, non-take-up rates for number of recipients are based on estimates published by the Department for Work and Pensions and HM Revenue and Customs.

In Estonia, it is assumed that small entitlements to the social assistance (either in absolute or relative to the household's other income) are not claimed.

In Finland, it is assumed that, although they can, grown-up children do not apply for income support separately from their parents. Also, households headed by the self-employed are assumed to not take up their entitlements.

In Latvia (paternity benefit) and Poland (housing benefit), simulated benefit entitlements are set to zero for those who do not report benefit receipt in the EU-SILC micro-data. Furthermore, to overcome the lack of information in EU-SILC on assets, needed to identify entitlement to the temporary social assistance, take-up is conditional on an estimated expected probability to be entitled to the benefit.

Tax non-compliance

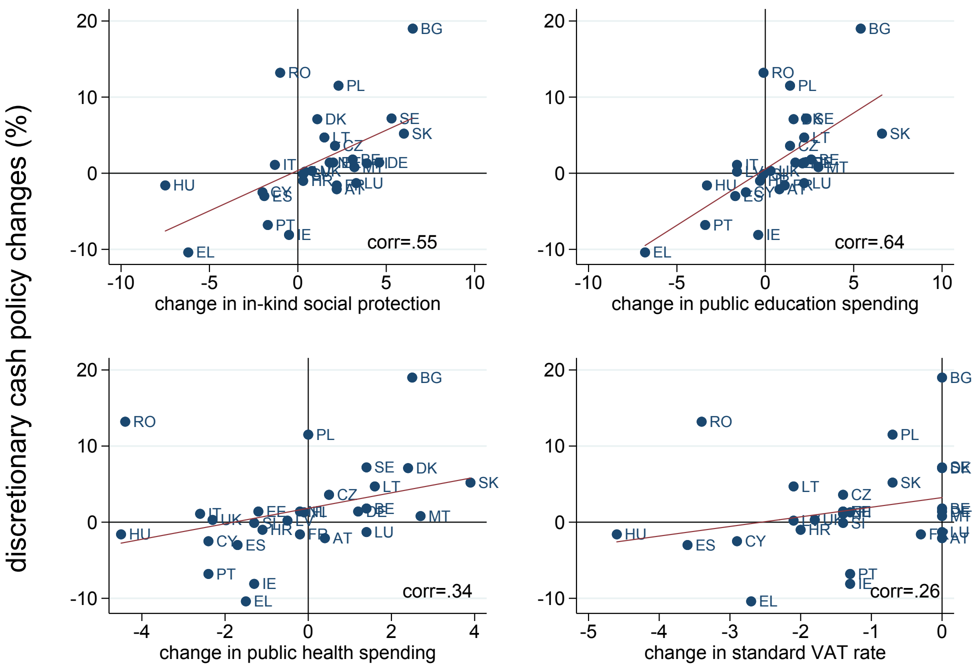
Tax non-compliance raises similar concerns as benefit non-take-up: if individuals fail to pay their tax liabilities, the distributional impact of taxes and tax reforms is affected. Also, non-compliance means that taxes cannot cushion shocks to earned income. Assuming full tax compliance, the number of tax payers and the stabilisation response of taxes would be overstated. To account for this, adjustments have been made to the income tax simulations in several countries in EUROMOD, where tax non-compliance may be most prevalent. Such adjustments are done in Bulgaria, Greece, Italy and Romania for the baseline simulations and maintained in our counterfactual simulations as well.

In Bulgaria, the adjustment is done based on a comparison between gross and net reported earnings. If identical, the assumption is that the person does not pay income tax and social insurance contributions. In Greece, adjustments are made based on external estimates for the extent of average underreporting of earnings and some types of self-employment income to the tax authorities. In Italy and Romania, adjustments are made to the extent people underreport self-employment income to the tax authorities.

For more details on the benefit non-take-up and tax non-compliance adjustments in EUROMOD, see the respective EUROMOD Country Reports available at `https://www.euromod.ac.uk/using-euromod/country-reports/f3-g4`.

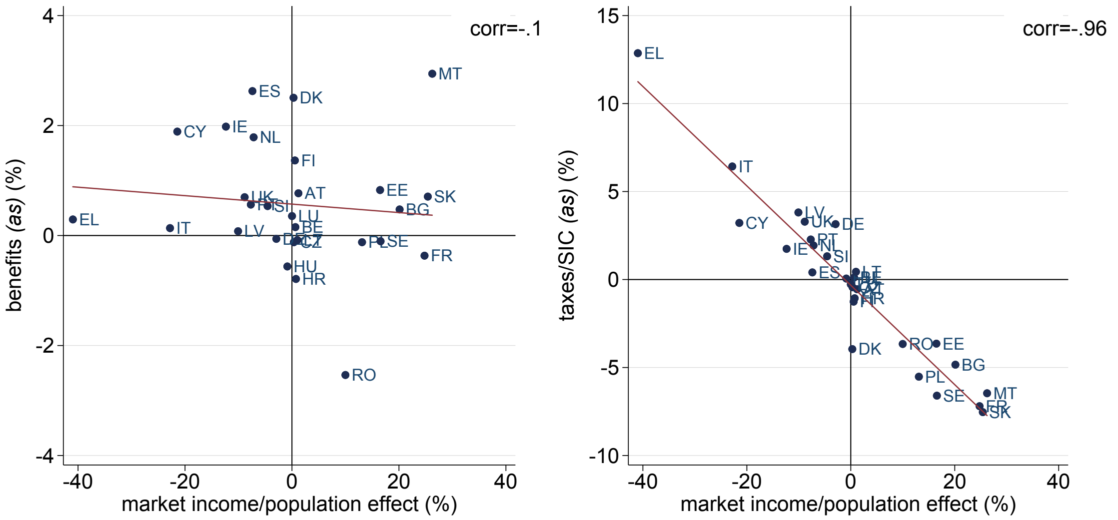
2.7.3 Decomposing income changes

Figure 2.9: Correlation of discretionary cash policy changes against changes to expenditure on in-kind benefits and VAT



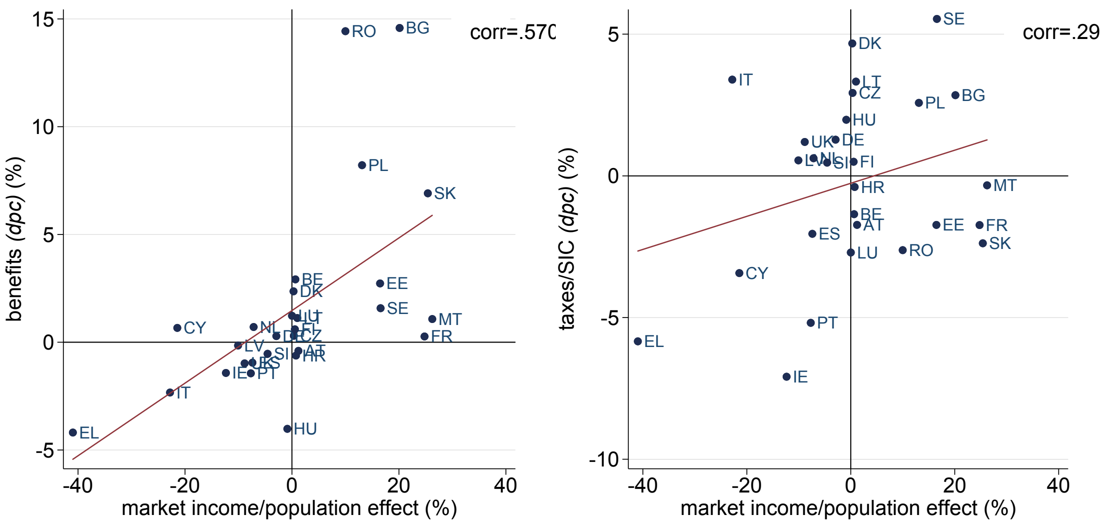
Source: Eurostat data on government spending on social protection (in-kind benefits) (indicator spr_exp_eur); health and education (indicator gov_10a_exp); population size for the respective country (indicator demo_pjan). The % change in mean income due to discretionary policy changes are based on authors' calculations using EUROMOD and EU-SILC and FRS data. *Notes*: Change in expenditures are presented in real terms per capita and as % of disposable income. The effect of the change in standard VAT rate is calculated assuming all income is spent on goods and services subject to the standard rate of VAT. The data on health and education includes both cash and in-kind payments. To calculate the change in per capita spending, total spending is divided by the population size for the respective country and year. The change in mean income due to discretionary policy changes is based on per capita income. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Figure 2.10: Correlation of automatic stabilisers by benefits and taxes/SIC against the market income/population effect



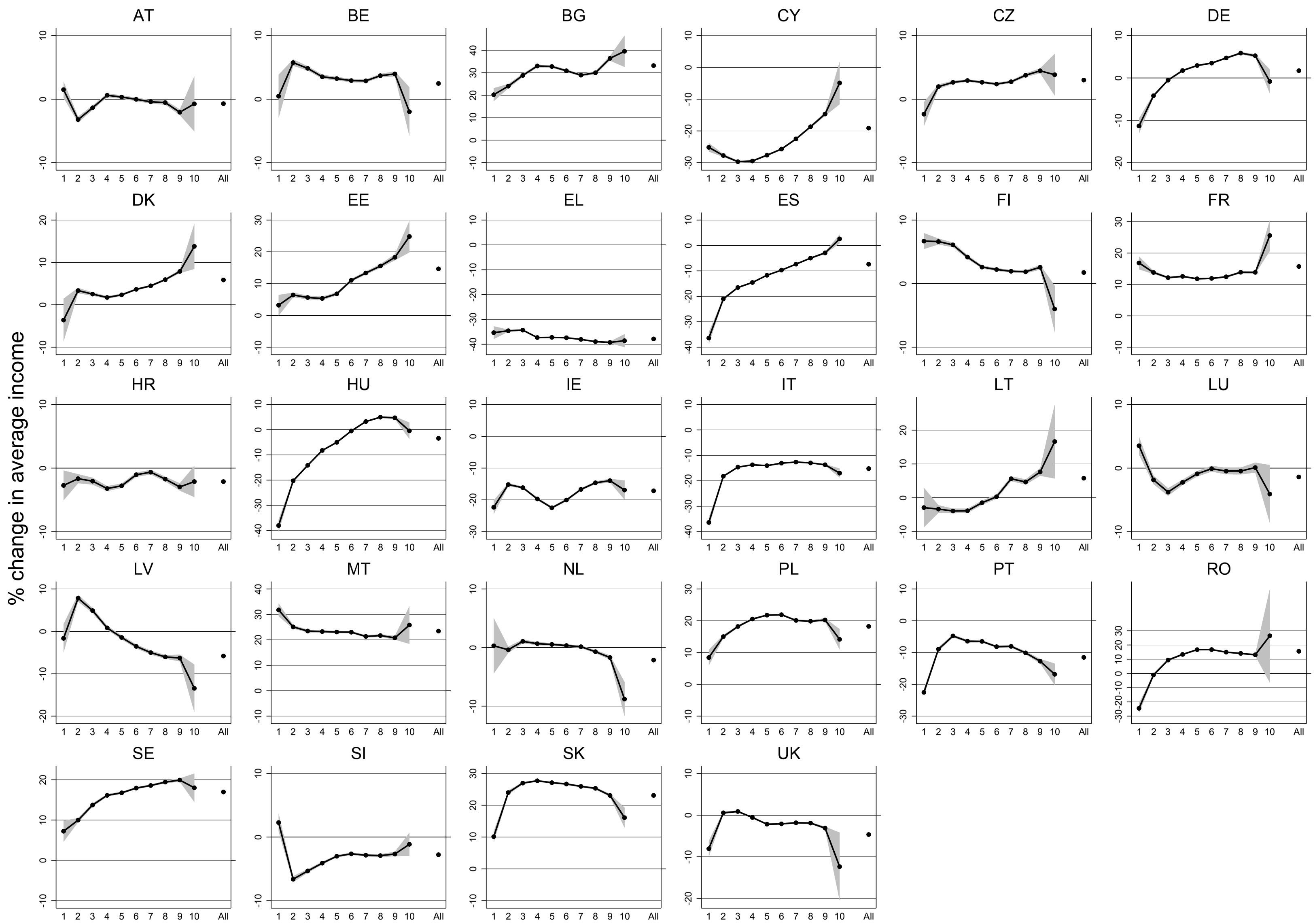
Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: as=automatic stabilisers. The vertical axis shows the % change in mean net income due to automatic stabilisers. The horizontal axis shows the % change in mean net income due to the market income/population effect. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Figure 2.11: Correlation of discretionary policy changes to benefits and taxes/SIC against the market income/population effect



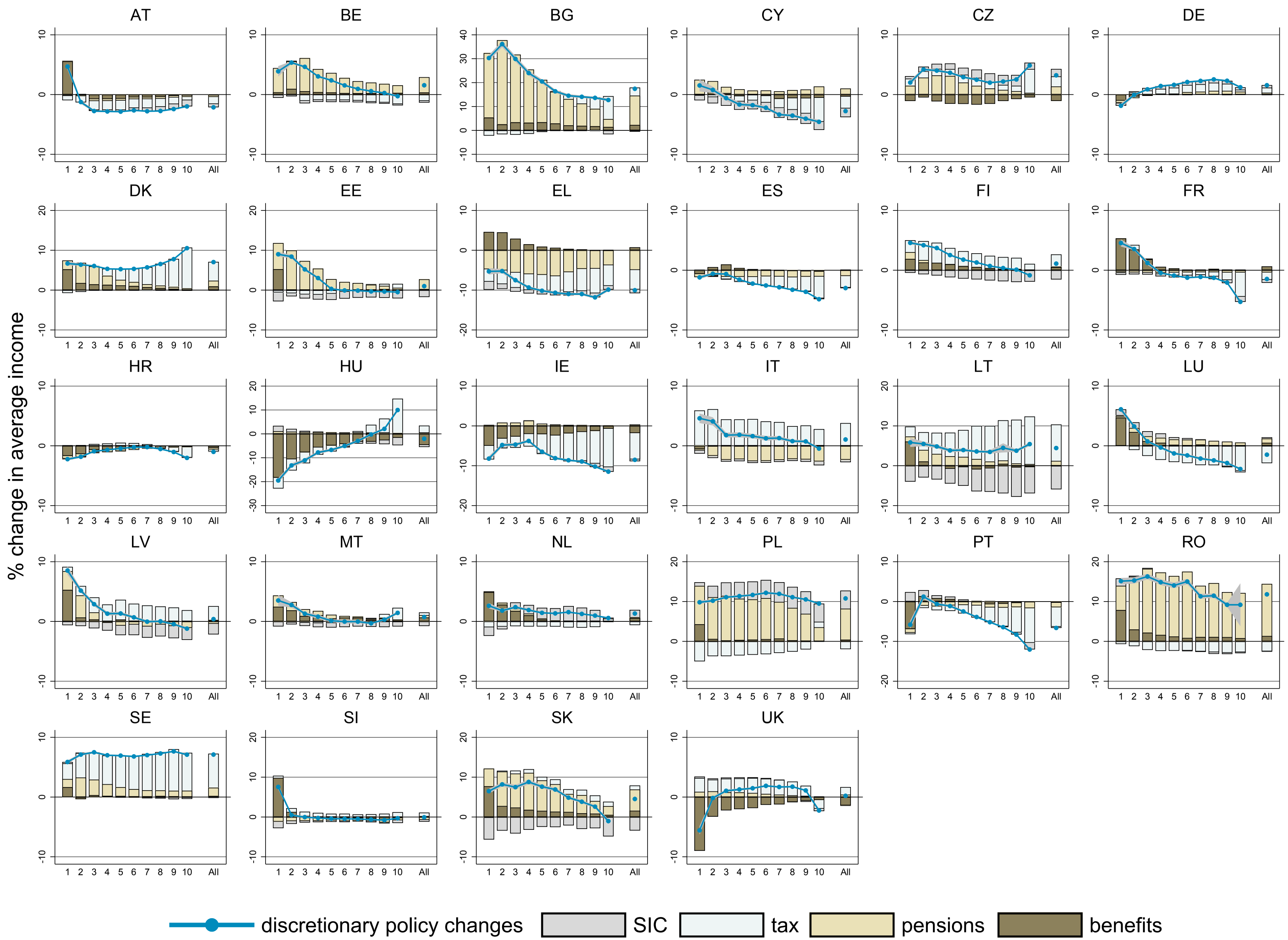
Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: dpc=discretionary policy changes. The vertical axis shows the % change in mean net income due to discretionary policy changes. The horizontal axis shows the % change in mean net income due to the market income/population effect. Changes to incomes are estimated in real terms. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Figure 2.12: Change in mean incomes by decile groups and country



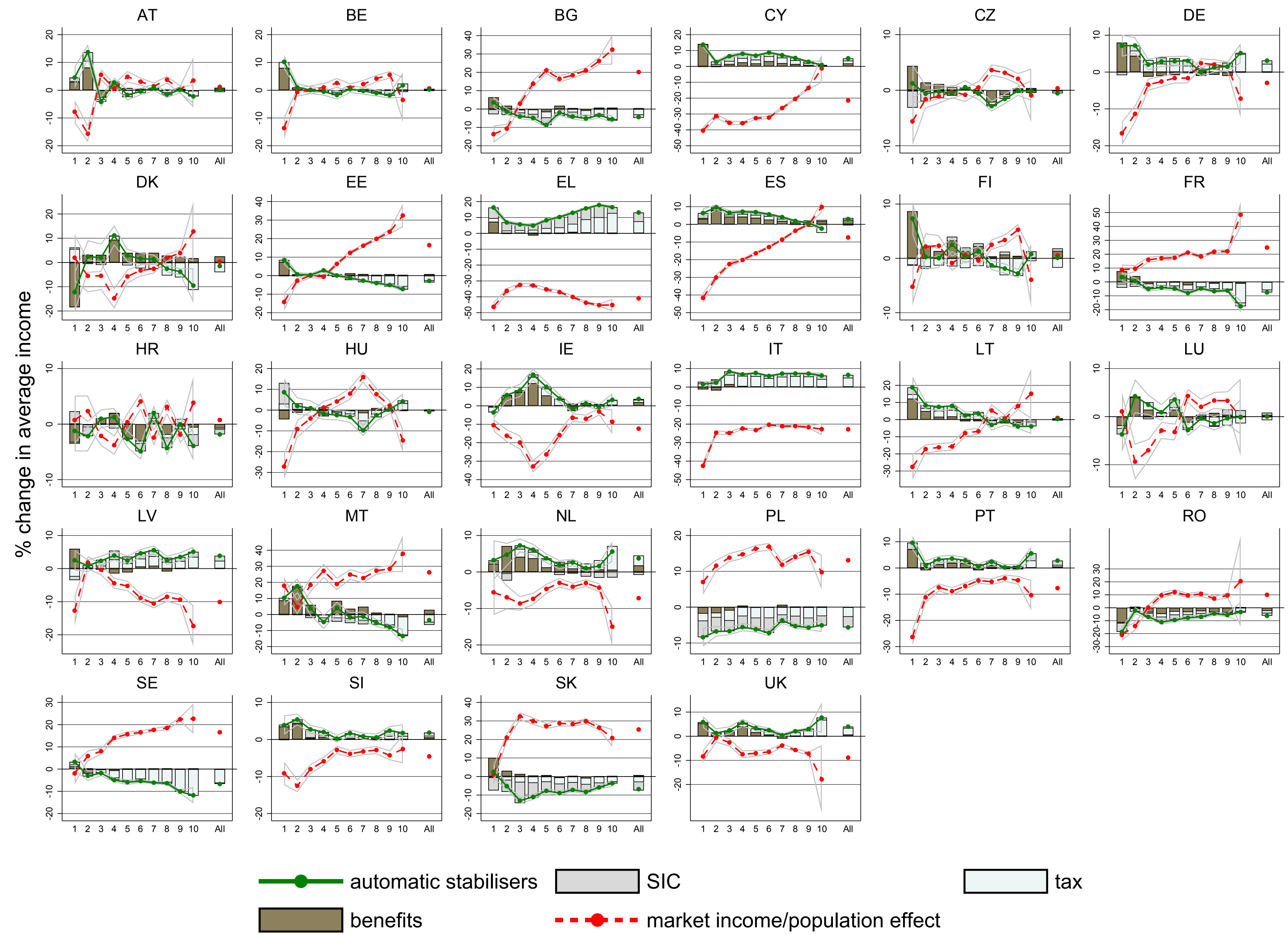
Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (2007/2014 actual) distribution of equivalised household net incomes. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Figure 2.13: Decomposing the effect on mean income of discretionary policy changes, by type of policy and decile group



Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (2007/2014 actual or counterfactual) distribution of equivalised household net incomes. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Figure 2.14: Decomposing the automatic stabilisation effect on mean income, by type of policy and decile group



Source: Own calculations with EUROMOD and EU-SILC/FRS. *Notes*: Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (2007/2014 actual or counterfactual) distribution of equivalised household net incomes. The reference period is 2007-2014 for nearly all countries and 2011-2014 for Croatia.

Chapter 3
Evaluating the Performance of Means-Tested Benefits in Bulgaria[1]

(published in 2016 in the Journal of Comparative Economics)

Abstract

Using household survey data and microsimulation techniques, we analyse the performance of three means-tested benefits in Bulgaria. We find that the transfers reach a small proportion of households with incomes below a relative poverty line, they have high non-take-up rates, and large proportions of the recipients are neither poor nor entitled to receive the benefits. Unsurprisingly, although an important income source for poor households, the benefits have a very small impact on reducing the poverty rates. We show that our results are robust to potential underreporting of benefit receipt in the household survey. Finally, we analyse the effect of five reform scenarios, one of which fiscally neutral, on poverty and find that there is a large scope for policy improvement.

Keywords: benefit non-take-up; leakage; means-tested benefits; poverty; microsimulation

JEL codes: D04, D63, I38

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3.1 Introduction

In recent years, poverty has been increasing in Bulgaria, rising in relative terms from 14 percent in 1999 to 21 percent in 2012 and in absolute terms from 1.2 million individuals in 1999 to 1.5 million individuals in 2012, despite a fall in the total population. In 2012, relative poverty in Bulgaria was among the highest in the EU, with an average poverty rate across the 28 member states of 17 percent. One of the reasons is the small impact that social transfers in Bulgaria have on poverty, estimated to be among the lowest in the EU. This poor performance of the social transfers may in turn partly reflect low levels of expenditures on social protection – in 2011 the total spending on social protection in Bulgaria was 16.9 percent of GDP, compared to an EU average of 28.3 percent, while the spending on means-tested benefits was only 0.7 percent of GDP in Bulgaria relative to 3 percent of GDP on average in the EU (Eurostat, 2014)[2] – but may also be due to poor design or implementation.

This paper provides a comprehensive assessment of the performance of means-tested benefits in Bulgaria using household survey data and microsimulation methods. We look at the largest three means-tested benefits in Bulgaria – the heating allowance (HA), guaranteed minimum income (GMI) and child allowance (CA) – and evaluate their performance in terms of targeting and poverty reduction. Several targeting issues are addressed. We measure the degree to which benefits are not taken-up by the entitled population (non-take-up) and to which non-entitled are among the benefit recipients (leakage). For those benefits which are means-tested, and therefore ought to target individuals on low incomes by design, we estimate how many of the poor are not being awarded with a benefit (exclusion of the poor) and how many among the recipients are in fact not poor (inclusion of the non-poor).[3] We show that our results on targeting are robust to underreporting of benefit receipt in the household survey data. Finally, we estimate the effect of the benefits on poverty.

Addressing targeting issues and thus understanding why benefits are not claimed by

[2]All figures from Eurostat database, 'At-risk-of-poverty rate by poverty threshold, age and sex (indicator: ilc_li02)'; 'At-risk-of-poverty rate before social transfers (pensions included in social transfers) by poverty threshold, age and sex (indicator: ilc_li09)'; 'Expenditure – Tables by functions, aggregated benefits and grouped schemes – in % of the GDP (indicator: spr_exp_gdp)'.

[3]The definition of being poor is defined with respect to the relative poverty line, which is 60% of the median equivalised household disposable income.

the entitled (or why they are received by the non-entitled) is important because this affects programme implementation and limits the extent to which policy goals can be achieved. Furthermore, if the reasons for not receiving are involuntary, such as imperfect information, high transaction costs or stigma, the groups intended to be targeted are not being treated equally by the welfare state (see, for a discussion, Oorschot, 1991). Equity issues will also arise if unintended and non-poor beneficiaries are awarded with a benefit, while the entitled and poor are excluded.[4] If such issues are present, policy makers cannot anticipate the true effect of policy interventions.

The paper enriches the analysis on the performance of means-tested benefits in Europe by providing some of the first estimates of non-take-up and leakage for an Eastern European country. Although there is a variety of means-tested benefits in Bulgaria to protect those at risk of poverty, to date there has been little empirical evidence on how successful these benefits are in reaching and protecting them (although see World Bank, 2009).[5] In particular, the ability of the programmes to target specific population groups (those entitled to the benefits) has remained unknown. Although there is a large literature estimating non-take-up of means-tested benefits and trying to understand the drivers of this behaviour (see, for example, Mangiavacchi and Verme, 2013; Bargain, 2012; Matsaganis et al., 2010), leakage rates have been rather neglected in the literature (for some exceptions see Benitez-Silva et al., 2004, and Kleven and Kopczuk, 2011).

In this analysis, we make use of household survey data combined with a tax and benefit microsimulation model. The former, namely the European Union Statistics on Income and Living Conditions (EU-SILC), tell us which households are receiving benefits in 2007; the latter allows us to identify the households in the EU-SILC that are entitled to receive means-tested benefits (as well as estimate the financial value of these entitlements). The tax-benefit microsimulation model used here is the Bulgarian component of the EU-wide microsimulation model EUROMOD (for more information on EUROMOD, see Sutherland and Figari, 2013). In addition, after analysing the status quo, we simulate five reform

[4]Depending on the policy rules, the entitled and poor can be overlapping groups but not necessarily the same. The same is valid for the non-entitled and non-poor.

[5]To the best of our knowledge, this is the only extensive empirical analysis on social assistance benefits in Bulgaria. The study provides an evaluation of the performance of social transfers in Bulgaria and it finds low levels of coverage among the poor with high levels of inclusion of non-poor recipients. However, the analysis does not provide any estimates on benefit non-take-up and leakage, i.e. the number of entitled who do not claim the benefits or the number of non-entitled among the benefit recipients.

scenarios to the existing benefits (one of which fiscally-neutral) as a way to explore the impact of policy changes on poverty and the scope for policy improvement.

Our main findings are as follows. First, we find that most of the spending and beneficiaries of the social assistance benefits, HA and GMI, come from the left tail of the income distribution. However, the programmes reach a very small proportion of the households with incomes below the relative poverty line. Recipients of the child benefit, CA, are distributed almost evenly across the deciles of the income distribution, due to its generous income-test. However, the benefit fails in providing income support to all poor households with families with children, leaving 30 percent of them unreached by the transfer. Second, we find that more than 40 percent of the intended beneficiaries of HA and GMI, and 30 percent of the intended beneficiaries of CA, do not take up benefits to which they are entitled.[6] We also find that a large proportion of beneficiaries report incomes which exceed the income-test threshold, and so should have disqualified them from entitlement. These results raise serious concerns about the quality of programme implementation. Third, the three benefits have negligible effect on the poverty rate: less than a 1 percentage point reduction. Moreover, we show that poverty rates would remain broadly unchanged even under a scenario of 100 percent benefit take-up and no leakage to the non-entitled. These results put Bulgaria among the worst performers in the region in terms of targeting the vulnerable and reducing poverty (see Avram, 2016). Finally, we consider the effect of five reform scenarios on poverty. Even a fiscally neutral scenario proves to be more effective than the current system in reducing poverty, showing that there is scope for policy improvement.

The paper is structured as follows. Section 3.2 provides a summary of the three means-tested benefits in Bulgaria. Section 3.3 describes the definitions of targeting, the methodology we adopt, the household survey data from EU-SILC and the tax-benefit microsimulation model EUROMOD. It also discusses the implications of benefit under-reporting in the survey data on the results and other data and microsimulation-related issues. Section 3.4 shows the results for targeting and poverty reduction. Section 3.5

[6]Reasons for non-take-up of benefits come from both the demand and supply side. Due to stigma, high transaction costs (long waiting time, queues etc.), and the low level of the benefits, entitled individuals could consider the application process too complicated or too costly and decide not to apply for the social transfers (Moffitt, 1983). On the supply side, excessive bureaucracy or complicated programme design can mean that benefits are not provided to the intended population (see Currie, 2006).

presents five alternative policy scenarios and analyses their effect on poverty. Section 3.6 concludes.

3.2 Means-tested benefits in Bulgaria

This section describes the details of the three benefits under study. These are the heating allowance, guaranteed minimum income and child allowance. The three benefits amount to 84 percent of the total budget for means-tested benefits in 2007 (see Boshnakov et al., 2012 and Eurostat, 2014).[7] Although there is a range of other means-tested cash and in kind benefits, they are not part of the analysis because their role in terms of income support provision is smaller or information on them is missing from the household survey data.

The **heating allowance** (HA) is given to the household and is intended to cover various groups of the population: single-person households, elderly, orphans, lone parents, families with children, students and individuals with disabilities. The benefit is paid each month for a period of 5 months during the winter. The applicant needs to fulfil conditions related to various demographic and economic characteristics such as age, health status, employment status, and household size, as well as assets. Furthermore, entitlement requires household income to be below a certain threshold where the threshold varies by individual characteristics and household type. This threshold is calculated as a percentage of a guaranteed minimum income level (gmil), which is defined as a minimum level for survival and amounts to 55 BGN per month in 2007 (28 EUR). The percentage rate varies from 120 percent for an adult living with her spouse to 240 percent for an elderly person. The benefit is paid at a rate common to all households (but varying by the heating source used by the household – electricity, central heating, natural gas or coal). The average benefit amount in the European Union Survey on Income and Living Conditions (EU-SILC) used for the analysis is 17 BGN per month (9 EUR or 8 percent of the relative poverty line).

The **guaranteed minimum income** benefit (GMI) is granted to households with

[7]For information on the total spending on means-tested benefits see Eurostat database, 'Tables by functions, aggregated benefits and grouped schemes – in MIO of national currency' (indicator: spr_exp_nac).

low incomes. Entitlement is defined in a similar way as for HA. The allowance is granted to households, which fulfil certain requirements related to demographic and economic characteristics, household size, assets[8] and whose household income is below a certain threshold. The threshold ranges from 30 percent of gmil for a child aged between 7 and 16 years, to 165 percent for an elderly person. If a household comprises of more than one individual, the sum of all thresholds for all individuals in the household represents the threshold for the whole household. The amount of the benefit equals the difference between the total household threshold and the gross household income; that is, the benefit is withdrawn with income. It is paid for 12 months. The household average monthly benefit amount in EU-SILC is 63 BGN (32 EUR or 30 percent of the poverty line).

The monthly **child allowance** for bringing up a child until completion of secondary school (CA) targets low income families with children. It is paid to families with child(ren) up to the age of 18 (or 20 if the child is enrolled in secondary school). The value of the income test in 2007 is 200 BGN per month (100 EUR) per family member. The benefit is provided to the family on a monthly basis. In 2007, its value is 18 BGN for the first child, 20 BGN for the second child and 20 BGN (in total) for the third and all subsequent children. The average monthly benefit amount per family in the EU-SILC is 24 BGN (12 EUR or 12 percent of the poverty line).

The income sources used in the income-test of the three benefits are: employment income, self-employment income, income from rent, public pensions, contributory benefits (for unemployment, sickness, pregnancy and childbirth, and maternity), and education scholarships. The benefits HA and GMI also enter the income-test for CA and vice versa. The application for the benefits is based on self-reported income (and other information). Applicants have to attach an income declaration issued by a relevant person or institution (e.g. the employer) as evidence. However, no evidence needs to be attached if zero income is reported in the application.

The objective of HA and GMI, as defined in the Law on Social Assistance (2012) (LSA), is to supplement or replace incomes and cover individuals basic needs defined as sufficient

[8] According to the conditions for the asset-test for both HA and GMI, the benefit claimant should: live in a dwelling composed of maximum 1 room per household member; not possess assets that can represent a source of income, except for the belongings that serve the usual needs of the family; not have contracts for a transfer of property in return for support and care (e.g. caring for lone elderly owners); not have acquired property through purchase or donation during the last 5 years.

amount of food, clothing and housing to survive. CA has the goal of providing income support for families with children. We could not find documentation on the methodology used to determine the value of the gmil, the thresholds for the various population groups or benefit levels. There are also no indexation rules in place for gmil and the size of the benefits.

3.3 Methodology and data

This section starts with the different definitions of targeting: non-take-up, leakage, exclusion of the poor and inclusion of the non-poor. After that, we explain our approach of combining household survey data with a tax-benefit microsimulation model, followed by a detailed description of the data and the model. We then focus on the issue of benefit underreporting in the survey data and describe the robustness checks we undertake. Finally, we validate the reported benefits in the household survey data and simulated benefit entitlements produced by the tax-benefit model using data from official administrative records.

3.3.1 Definitions of targeting

Our approach is to assess the extent of vertical and horizontal targeting efficiencies. They imply that only the poor, and all the poor, should be awarded with a means-tested benefit. We measure two targeting errors related to these concepts: the rate of inclusion of the non-poor, and exclusion of the poor. Additionally, two more types of targeting errors are calculated: benefit non-take-up (two definitions are considered following Brewer (2003) and Bargain et al. (2012)) and leakage to non-entitled households.

Starting with the last two definitions, estimating benefit non-take up and leakage rates is crucial in assessing the performance of transfer programmes because they affect programme implementation and policy goals achievement. Non-take-up can be measured in two ways. First, it can be the fraction of people entitled to receive a benefit, but not provided with it.

$$R_{\text{non-take-up1}} = \frac{N_{\text{entitled,not in receipt}}}{N_{\text{entitled}}} \tag{3.1}$$

where $N_{\text{entitled,not in receipt}}$ is the number of entitled households (or households with entitled families as in the case of CA) who did not receive the benefit and N_{entitled} is the total number of intended beneficiaries (those in receipt and not in receipt).

The second type of non-take-up rate:

$$R_{\text{non-take-up2}} = \frac{N_{\text{entitled,not in receipt}}}{N_{\text{in receipt}} + N_{\text{entitled,not in receipt}}} \tag{3.2}$$

expresses the total number of households eligible for the benefit, but not in receipt of it, as a percentage of the sum made up of those receiving the benefits (whether entitled or non-entitled) and those entitled but not reporting receipt. This definition of non-take-up acknowledges that some of the recipients may not be assessed as entitled due to error in identifying them or that some of the recipients may be truly non-entitled due to leakage. The denominator of the second non-take-up rate is equal or larger than the denominator of the first non-take-up rate and so estimates for this indicator are equal or lower, respectively, than for the first definition. In the literature, these two rates are combined to show in a way an upper (definition 1) and lower (definition 2) bounds of non-take-up (see Brewer (2003) and Bargain et al. (2012)).

The leakage rate is defined as the non-entitled households who receive a social transfer ($N_{\text{non-entitled,in receipt}}$) as a proportion of all beneficiaries ($N_{\text{in receipt}}$):

$$R_{\text{leakage}} = \frac{N_{\text{non-entitled,in receipt}}}{N_{\text{in receipt}}} \tag{3.3}$$

To calculate the extent of exclusion of the poor, and inclusion of the non-poor among beneficiaries, we use a poverty line of 60% of the median equivalised household disposable income, and denote individuals in households with incomes lower than the poverty line as being poor. Regarding horizontal equity, the definition of the exclusion error refers to the proportion of poor not in receipt of a social transfer. This rate estimates the capacity of the programmes to correctly identify the poor. The exclusion error equals:

$$R_{\text{exclusion of the poor}} = \frac{N_{\text{poor,not in receipt}}}{N_{\text{poor}}} \tag{3.4}$$

$N_{\text{poor,not in receipt}}$ is the number of households with income below the relative poverty line who did not receive the benefit and N_{poor} is the total number of poor households below the relative poverty line (or poor households with families with children as in the case of CA).

The inclusion error looks at how many of the programme recipients were not poor before receiving the benefit. The rate is equal to the following fraction:

$$R_{\text{inclusion of the non-poor}} = \frac{N_{\text{non-poor,in receipt}}}{N_{\text{in receipt}}} \tag{3.5}$$

where $N_{\text{non-poor,in receipt}}$ is the number of non-poor households who receive the benefit.

To be able to estimate benefit non-take up and leakage, we require information at the individual or household level on 1) who actually receives the benefit and 2) who is legally entitled to receive it. Information on the former can be found in the data from the European Union Survey on Income and Living Conditions (EU-SILC) used for the analysis, where households report different sources of incomes. However, EU-SILC, similar to any other survey, does not ask households/individuals if they are entitled to a benefit. This information can be only acquired through a tax-benefit microsimulation model which calculates entitlements based on information on household circumstances available in the survey data and knowledge of the benefit legislation. We discuss our approach in more detail below.

3.3.2 Data description

The household survey data are from the European Union Survey on Income and Living Conditions (EU-SILC). EU-SILC is the largest and most detailed household income survey existing at the moment in Bulgaria. It is used by the National Statistical Institute for official statistics on social inclusion and living conditions. The data are nationally representative and contain individual and household level information on demographic and socio-economic characteristics and incomes from various sources such as (self-)employment, pensions and benefits. The data we use are collected in 2008 with income reference period 2007. EU-SILC used in this analysis is a combination of the User Data Base SILC, which contains aggregate information about benefits, and some national SILC variables, which provide data about the separate benefit components. For a detailed data description, see Appendix 1.

3.3.3 EUROMOD

The entitlements to means-tested benefits for each household in the EU-SILC are calculated by EUROMOD. The model consists of components for each EU member state. It operates based on nationally representative household survey data. By using information on household and individual characteristics and market incomes taken from the data and combining it with country-specific legislation rules, the model calculates (simulates) household and individual-level benefit entitlements, tax and social insurance liabilities as well as household disposable income (for a detailed model description, see Sutherland and Figari, 2013). EUROMOD has been widely used in the economics literature (for recent publications see e.g. Bargain et al., 2014; Dolls et al., 2012). It has also been used to estimate non-take-up rates in Greece and Spain (Matsaganis et al., 2010). To calculate benefit non-take-up and leakage rates, we compare information on receipt of the three means-tested benefits observed in the survey data with simulated entitlements to the same three benefits as calculated by EUROMOD, all for a given household.

The definition of household disposable income used throughout the analysis includes the sum of market income (income from employment, self-employment, property (rent), net private transfers (private transfers received minus maintenance payments), interest, other (income received by children under 16)), pension income (benefits for old-age, survivor and disability), other benefits (for unemployment, maternity, sickness, family, social assistance, housing, education), income from agricultural and own production, minus income tax, property tax and social insurance contributions.

3.3.4 Accounting for benefit underreporting

When using household survey data and microsimulation techniques, five issues could bias the results. Measurement error in the data and the simulations may drive the bias in different directions. First, EU-SILC does not collect enough information on assets to allow the simulation of all eligibility criteria for HA and GMI. In the absence of data, we assume the household meets that particular criterion. As a result, the following two biases may arise: First, if non-entitled recipients are misclassified as entitled recipients, the numerator in the calculation of leakage will go down while the denominator in the calculation of non-take-up based on the first definition only will go up which would result in both leakage and non-take-up being underestimated. Second, if non-entitled non-recipients are wrongly classified as entitled non-recipients, the numerator in the formula for non-take-up based on both definitions will increase (more relatively to the denominator) and non-take-up will be overestimated.

Second, a known problem of survey data on incomes is that it may fail to cover individuals at the very bottom of the income distribution (e.g. people not living in households). In this case then our results may be biased in either direction, depending on the size of the excluded population and the number of (non-)entitled (non-)recipients among them.

Third, a general sort of error can occur if there are errors in the calculations done by the microsimulation model (for example, a mismatch between the data reference period in the survey data and the time period when the income-test has been applied); these could cause biases in any direction.[9]

Fourth, we typically think the prevailing measurement issue in survey data is income underreporting (see for a recent analysis Brewer et al. (2017) and Meyer et al. (2015)). Underreporting of those sources of income, that are used to assess entitlements to benefits, could result in the following biases (similar to the biases described under the first point): If non-entitled recipients underreport incomes, so they are misclassified as entitled recipients,

[9]For GMI and HA, the income-test refers to incomes from previous month. There is no information in the data, on when benefit receipt started and the available data are only for 2007. For the income-test, we used therefore average monthly incomes for 2007, although there might have been fluctuations over the months, which are not considered, and the income-test might have referred to incomes from 2006, which are not observed. It is not clear, though, in which direction the results will be biased.

then both non-take-up based on the first definition and leakage will be underestimated (the denominator in the formula for non-take-up will increase, while the numerator in the leakage rate will decrease). If non-entitled non-recipients underreport incomes, so they look like entitled non-recipients, then the numerator in the calculation of non-take-up (both definitions) will increase more relatively to the denominator and so, non-take-up will be overestimated. There will be no impact on these rates if households entitled recipients or entitled non-recipients are not misclassified even though they underreport incomes. Appendix 1 gives more details on the EU-SILC data, and a comparison between EU-SILC and national accounts data. To sum up, we find limited evidence on the extent of income underreporting in EU-SILC and among the recipients of HA, GMI and CA. This does not allow us to measure the direction or size of a potential bias in the results.

Finally, an important concern for the validity of the results is the issue of benefit underreporting (see Lynn et al. (2012) on the incidence of benefit underreporting and ways of reducing it in panel data). Benefit underreporting may refer either to a household reporting a lower amount of the received benefit or to a household declaring falsely that it has not received a benefit at all. When calculating non-take-up and leakage only the second type of benefit underreporting may bias our results: If the benefit of interest has been underreported only by entitled households, then non-take-up and leakage will be overestimated. However, if the benefit has been underreported only by the non-entitled (i.e. there genuinely is leakage but it is underreported in the survey), then results for leakage will be underestimated while non-take-up based on the second definition will be overestimated.

Due to lack of administrative data, none of these biases can be measured and so the magnitude of the error is, in general, not verifiable. However, we can address the issue of benefit underreporting, i.e. not reporting to have received a benefit, which we believe may be one of the largest concerns.

We proceed by noting two discrepancies. First, the total number of reported benefit recipients in the EU-SILC data is lower than the total number of households that are simulated to be entitled (by EUROMOD). Second, the total number of reported benefit recipients in the EU-SILC data is also lower than the total number of recipients according to administrative figures (see next subsection). Let us assume that this is entirely due to benefit underreporting in EU-SILC. Thus, the magnitude of underreporting can be quantified according to either the first or second discrepancy.

We consider the following five scenarios: a baseline scenario with no correction for underreporting, and scenarios for which we assume that benefits have been underreported in EU-SILC by non-recipients who are i) entitled, ii) non-entitled, iii) poor, or iv) non-poor. We impute benefit receipts (by random selection) for each scenario separately, so that non-recipients are transformed into recipients. As a result, there is an increase in the number of recipients in EU-SILC who are i) entitled, ii) non-entitled, iii) poor, or iv) non-poor. The number of imputed benefit receipts depends on the two discrepancies: according to the first one, the number of benefit recipients in EU-SILC would equal the number of households with a simulated entitlement; according to the second one, the number of benefit recipients in EU-SILC would match the number of recipients from administrative statistics. Scenarios i) to iv) represent the extremes and we have selected these to calculate lower and upper bounds around the targeting error rates. Scenarios i) and ii) provide bounds around non-take-up and leakage, while scenarios iii) and iv) provide bounds around the rates of exclusion of the poor and inclusion of the non-poor.

The imputations under scenario i) will provide a lower bound for benefit non-take-up and leakage: as the number of entitled recipients goes up, the numerator in the formulae for non-take-up (i.e. the number of entitled non-recipients) will go down and so, non-take-up will fall. In terms of leakage, the denominator in the formula (i.e. all recipients) will increase and so, the rate will fall. Scenario ii) will provide us with an upper bound for leakage: the numerator in the leakage rate (i.e. the number of non-entitled recipients) will increase more relatively to the denominator (i.e. all recipients) and so, leakage will increase. Non-take-up based on the first definition will not change because of non-accountability of non-entitled in the calculation. Non-take-up based on the second definition will fall as the denominator (i.e. the number of recipients plus entitled non-recipients) will increase.

Under scenario iii) a lower bound for the rates of exclusion of the poor and inclusion of the non-poor will be calculated: as the number of poor recipients among all poor increases, the rate of exclusion of the poor will go down. In addition, the denominator in the rate of inclusion of the non-poor (i.e. all recipients) will also increase and so, the rate will go down.

Finally, under scenario iv) an upper bound for the rate of inclusion of the non-poor will be generated: the numerator in the rate (i.e. the number of non-poor recipients) will increase more relatively to the denominator (i.e. all recipients) and so, the rate of inclusion of the non-poor will increase. The rate of exclusion of the poor will remain the same, because non-poor are not taken into account in the calculation.

3.3.5 Data comparisons and related issues

In this subsection, we validate the simulated benefit entitlements produced by the EUROMOD model and reported benefits in EU-SILC using data from official administrative records with a view to understand if there is benefit non-take-up or leakage. Table 3.1 compares the number and total amount of simulated entitlements (calculated by EUROMOD) with the number of benefit recipients and total spending recorded in EU-SILC, and the corresponding totals of recipients and spending recorded in administrative data. We observe that the number of simulated social assistance entitlements is less than the number of recipients from administrative figures (the ratio is 0.69 for HA and 0.73 for GMI, see ratio (1/2) in panel A); this could be an indication that part of the benefits may be distributed to non-entitled recipients (i.e. there is benefit leakage). In contrast, the number of simulated CA entitlements is higher than the number of CA recipients from administrative figures (the ratio is 1.11): this discrepancy points to the possibility of benefit non-take-up.

Comparing the number of benefit recipients from EU-SILC with those from the administrative figures (ratio (4/2)) in panel A suggests that all benefits might be underreported in EU-SILC. On the other hand, the number of recipients from EU-SILC is lower than the number of simulated entitlements, which could also indicate benefit non-take-up. Moving on to panel B of Table 3.1, ratio (1/2) shows the total amount of simulated entitlements from EUROMOD over the total spending from administrative figures. As the ratios for HA and GMI are lower than 1, this indicates that the spending of the two benefits has been undersimulated by EUROMOD; the ratio for CA is 1.07 meaning that the total spending for CA is slightly oversimulated. This is in line with the findings in the paragraphs above. In the case of the three benefits, ratio (1/2) is higher than ratio (4/2), implying that the average simulated entitlements are higher than the average amount of benefit receipt reported in the underlying micro data EU-SILC.

[place Table 3.1 here]

Table 3.2 compares the mean monthly values of the benefit entitlements, separately for those reporting positive amounts in EU-SILC and for those simulated to be entitled by EUROMOD. In the case of HA, which is paid at a rate common to all households, the average reported value of the benefit and simulated entitlements are close to identical.[10] GMI and CA are not paid at a common rate to all households: the GMI amount depends on household incomes, while the CA amount depends on the number of children. Table 3.2 shows that the mean simulated unclaimed entitlement (for those simulated eligible but not reporting a positive amount) for both benefits is lower than the mean simulated claimed entitlement (for those simulated eligible and reporting a positive amount). This is in line with the idea that a higher entitlement to benefits helps offset the (actual or opportunity) costs of claiming benefits, e.g. the cost of collecting necessary application documents, long waiting times and stigma.

[place Table 3.2 here]

3.4 Results

This section presents the main results and assesses the performance of the benefits across several dimensions. It starts with looking at the benefit incidence across the income distribution. The analysis moves on to targeting issues, by providing estimates for benefit non-take-up, leakage to non-entitled claimants, exclusion of the poor and inclusion of the non-poor among the benefit recipients. The results are demonstrated to be robust to an adjustment for benefit underreporting in the data if the adjustment is based on the

[10] The small discrepancy can be explained as the average benefit duration assumed by EUROMOD is the maximum possible and it is slightly higher than the average benefit duration reported in the data.

difference between the number of reported claimants in EU-SILC and the total number of simulated entitlements by EUROMOD. If the adjustment is based on the difference between the number of recipients in EU-SILC and administrative figures, the bounds of the estimates for social assistance increase and the results become less robust, while the opposite is true for the child benefit. The final part of the section compares the pre-transfer and post-transfer poverty figures, providing a discussion on the impact of the benefits on poverty in Bulgaria.

3.4.1 Benefit incidence

This subsection shows the incidence of the three benefits across the income distribution. Individuals are ranked based on their equivalised household disposable income before receiving each one of the transfers in turn.

Figure 3.1 shows the distribution of spending on HA, GMI and CA as reported in EU-SILC (the grey lines) alongside the total amount of simulated entitlements by EUROMOD (the black lines). The figure shows that based on EU-SILC, all three benefits target the poor well. GMI performs best with 77 percent of its spending going to the poorest two deciles. A similar picture emerges for HA with 69 percent of the budget going to the poorest two deciles of the income distribution. In terms of CA spending, 26 percent is transferred to the bottom two income deciles. This is in line with the design of the benefit high income-test which aims at reaching families from the higher tail of the income distribution.

[Figure 3.1 here]

Figure 3.2 repeats the exercise but for benefit receipt: 74 percent of GMI and 69 percent of HA recipients come from the bottom two income deciles, but CA reaches the poor to a lesser extent as only 25 percent of CA recipients come from the poorest two deciles. Contrasting this to Figure 3.1, the results suggest that the mean value of GMI is slightly higher for the lower 2 deciles than for the rest of the distribution. The value of HA is equal across recipients, given that it is a uniform benefit paid at the household level. The mean value of CA is larger for the poorer deciles because of larger number of children in poorer households.

[Figure 3.2 here]

Turning to the results of the simulated benefit entitlements, we see that the distribution of the simulated GMI and HA is even more concentrated in the first two income deciles, making them more progressive than the benefits reported in EU-SILC. The distribution of the simulated CA is also more concentrated at the bottom part of the distribution making it appear more progressive than actual receipt as reported in EU-SILC. Assuming that there are no programme implementation errors, one would expect that the distribution of the reported benefits and simulated entitlements (both spending and recipients) to be identical. The next subsection addresses this puzzle.

3.4.2 Targeting

The previous indicators offer only limited information about the performance of the benefits in terms of targeting, the extent to which the actual distribution of a benefit corresponds to the desired distribution. Given that the benefits are aimed at satisfying the basic living needs of the individuals, it is important to see what proportion is given to the entitled and/or poor and what proportion is given to the non-entitled and/or non-poor.

The estimates for the targeting errors i.e. non-take-up, leakage, exclusion of the poor and inclusion of the non-poor, together with their standard errors, are shown in Table 3.3. Based on the first definition of non-take-up (the proportion of entitled non-recipient over all entitled households), the non-take-up rate amounts to large 66 percent for HA and 73 percent for GMI, and 39 percent for CA. The substantial non-take-up rates of HA and GMI are in line with the qualitative analysis in Bogdanov and Zahariev (2009) which suggests that the high complexity of the programmes causes confusion for the social workers, who are forced to deal with an enormous amount of paper work. This could result in incorrectly turning down applications by otherwise entitled households. Similarly, claimants of social assistance report that the application process is very long and cumbersome and that the benefit amount is too low to provide sufficient income support.

When we compare the estimates for the first definition with the ones for the second definition of non-take-up (the proportion of entitled non-recipient over all recipient and entitled non-recipient households), some key differences between the two are revealed. In line with the non-take-up rates under definition 1, the rates under definition 2 are the highest for HA and GMI (41 percent and 47 percent, respectively). However, in contrast to CA, there is substantial difference under the two definitions for HA and GMI. This suggests a potentially large leakage to the non-eligible population for these two benefits.

In comparison to non-take-up of means-tested benefits in other countries, the estimated rates in Bulgaria are relatively high. Non-take-up for social assistance is of similar size to the rates (definition 1) in Germany (63 percent for Social Assistance in 1993 (Riphahn, 2001)) and Greece (63 percent for pensioner social solidarity benefit and 38 percent for pension to uninsured elderly in 2004 (Matsaganis et al., 2010)). In Spain, Australia and Finland, on the other hand, benefit non-take-up is smaller compared to the estimates for HA and GMI: based on definition 1, 22 percent for supplements to reach the minimum and 44 percent for non-contributory old-age pensions in 2004 in Spain (Matsaganis et al., 2010); 15 percent for Income Support and 29 percent for Parenting Payment in 2002 in Australia using definition 1 (Mood, 2006); and between 43 percent (definition 2) and 51 percent (definition 1) for social assistance in 2003 in Finland (Bargain et al., 2012). In the UK, the Department for Work and Pensions (DWP) has been publishing benefit take-up estimates ranges until 2009/10. We have translated these into non-take-up rates based on definition 2 and the extent of the issue varies depending on the benefit: 11-23 percent for Income Support and Employment and Support Allowance, 20-27 percent for Guarantee Credit, and 16-22 percent for Housing Benefit (DWP, 2012). The evidence about the USA is also somewhat mixed, depending on the benefits (see Currie (2006) for an overview).

Moving to leakage, the proportion of non-entitled recipient over all recipient households, the rate equals 64 percent for HA and 68 percent for GMI. Although recipients are mostly in the first two income deciles, the estimate of leakage is high because the programmes are targeted at the first income decile only. Thus, whilst we see high non-take-up rates for HA and GMI amongst the targeted population, a substantial number of households who do not fulfil the income-test are in receipt of social assistance. In contrast, the estimated leakage rate for CA is lower at 19 percent reflecting the fact that a larger share of the population is eligible for the benefit.

We consider three possible channels through which the high leakage of HA and GMI could occur. First, the confusion among social workers due to the complex benefit rules (see Bogdanov and Zahariev, 2009) could not only result in falsely rejecting applications by entitled households but also accepting applications by ineligible households. Second, corruption through bribes could be another channel through which benefits are transferred to non-entitled households. Although there are no estimates on the size of corruption in Bulgaria, a few studies suggest very high public perception levels.[11] The third channel could be related to the informal economy in Bulgaria in terms of underdeclaring income to authorities in order to avoid the payments of taxes or to receive benefit entitlements. Although there is no conclusive evidence on the size of informal economy in the country, again there is evidence on high public perception levels.[12]

Worryingly, the results also show that very large numbers of the poor are excluded from the social assistance benefits: 77 percent for HA and 94 percent for GMI or in other words, only 23 percent and 6 percent of the poor receive HA and GMI, respectively. In comparison, the results for 2007 by the World Bank (2009) show similarly that the exclusion error of HA and GMI is equal to 87.9% and 88.6%, respectively.[13] Although HA and GMI are mainly provided to the poor, their coverage is very low. Avram (2016) estimates the percentage of poor receiving social assistance for 8 Central and Eastern European countries using the cross-sectional component of EU-SILC for 2008. She finds very low coverage of the poor in the three Baltic countries, Estonia (8 percent), Latvia (16 percent) and Lithuania (20 percent). In the Czech Republic, Poland, Slovakia and

[11]For example, for a study on public perceptions of corruption levels see Eurobarometer report (2008): 'The attitudes of Europeans towards corruption', Special Eurobarometer 291, available at: http://ec.europa.eu/public_opinion/archives/ebs/ebs_291_en.pdf. The study shows that in 2007 92% of the respondents agree with the statement that corruption is a major problem in Bulgaria. This puts the country on place 5 (out of 27) with EU27 average score of 75%. Between 82% and 85% of the respondents agree with the statement that there is corruption at local, regional or national institutions (with EU27 average score of 73% to 77%). Bulgaria also scores about two times the EU27 average on the question if 'giving and taking of bribes, and the abuse of positions of power for personal gains are widespread among': the people working in the judicial, police or custom services, public health or education sectors. For other studies which show high levels of perceived corruption in Bulgaria, see http://www.transparency.org/research/cpi/cpi_2007/0/.

[12]For a study on employers and employees perceptions on the size of informal economy in Bulgaria see Bulgarian Industrial Capital Association (2012): 'The first monitoring report on the informal economy and progress achieved in its prevention', available in Bulgarian at: http://www.ikonomikanasvetlo.bg/c/document_library/get_file?uuid=cc8fb441-d183-42a5-b4b9-14241cf5cd76&groupId=55360. There is also a study by Buehn and Schneider (2012) which estimates the size of shadow economy in Bulgaria in 2007 at high 32.7%.

[13]The discrepancy in our and the World Bank (2009) results are likely to be due to differences in the survey data used in the analysis, in the definition of household disposable income and as a result, in the value of the relative poverty line.

Slovenia, the coverage rate varies between 26 percent and 37 percent, while in Hungary it is found to be 46 percent. The findings suggest that social assistance benefits in Bulgaria, despite having the aim of covering basic needs and providing income support to the poor, have a low coverage of the poor similar (or worse) to the ones in the Baltic countries.

The exclusion of poor households (with families with children) is 30 percent for CA, showing that it has a better coverage. We see that the smallest coverage of the poor occurs among the benefits with the highest leakage. This is an important finding, as it suggests that the coverage of the poor could be improved, by better targeting the benefits on poor households only (at no additional cost).

The results for the inclusion of the non-poor are 34 percent for HA and 27 percent for GMI. In regard to this indicator, Bulgarian benefits are characterized with lower error in comparison to their counterparts in the other countries; the inclusion errors estimated by Avram (2016) are 30 percent for social assistance benefits in Lithuania, around 38 percent in the Czech Republic, 37 percent in Slovakia, 44 percent in Poland, 49 percent in Estonia, 54 percent in Latvia, and more than 60 percent in Slovenia and Hungary. This might well be due to the higher income-test and larger population coverage of the schemes in the other Central and Eastern European countries Avram (2016). The inclusion of the non-poor is significantly higher for CA: the rate is estimated at 78 percent. This supports the above evidence showing substantial room for poverty reduction, by better targeting the available funds to the poor.

The results are remarkable because the programmes are characterised by both high non-take-up and leakage, and both inclusion and exclusion errors. Elderly, people of working age, children, lone parents, parents of small children, and people with disabilities are targeted according to the programmes' design, and, yet, the coverage of the entitled and poor remains low, while leakage and inclusion of the non-poor is high.

[Table 3.3 here]

3.4.3 Robustness checks

In Section 3.3, Table 3.1 showed that for the three benefits, the number of observed receipts in the EU-SILC data is lower than both the total number of simulated entitlements by

EUROMOD and the number of recipients from administrative figures. We assume that these differences are entirely due to benefit underreporting, i.e. not reporting to have received a benefit (as opposed to reporting lower benefit amounts), in EU-SILC. In this way, we test the sensitivity of our results on the targeting error rates: non-take-up, leakage, exclusion of the poor and inclusion of the non- poor.[14]

As described in detail in Section 3.3, we look at the following five scenarios: the baseline scenario with no correction for underreporting, and scenarios where the benefits have been underreported in EU-SILC by non-recipients who are i) entitled, ii) non-entitled, iii) poor, or iv) non-poor. We impute benefit receipts for each scenario separately, so that non-recipients are transformed into recipients. As a result, there is an increase in the number of recipients in EU-SILC who are i) entitled, ii) non-entitled, iii) poor, or iv) non-poor. Scenarios i) and ii) provide bounds around non-take-up and leakage, while scenarios iii) and iv) provide bounds around the rates of exclusion of the poor and inclusion of the non-poor. The number of imputations is such that the total number of benefit receipts (both reported and imputed) in EU-SILC matches in the first case, the total number of simulated entitlements by EUROMOD and in the second case, the total number of benefit receipts according to administrative figures. Table 3.4 and Table 3.5 report how the targeting error rates change according to the first and second case, respectively.

[Table 3.4 here]

[Table 3.5 here]

The range of the bounds for HA and GMI in Table 3.4 is much smaller than in Table 3.5: this is because the discrepancy between the number of benefit receipts reported in EU-SILC and entitlements calculated by EUROMOD is smaller than the discrepancy between the number of receipts in EU-SILC and according to administrative records. The opposite is true for CA. Table 3.4 shows that after accounting for benefit underreporting the results remain robust with one exception in the case of CA the lower bound for the exclusion of the poor equals 0.

[14]In addition, Appendix 2 reports the results from another sensitivity check based on simulations of measurement error in the income data. The results provide some limited evidence that suggests that the estimates on non-take-up and leakage in this analysis cannot be explained by measurement error in the data. We thank an anonymous referee for the suggestion to implement these simulations.

In Table 3.5, the rate of non-take-up 1 for HA and GMI is within a much larger range than as shown in Table 3.4. In Table 3.4, the range is between 60-66 percent for HA and 56-73 percent for GMI. In Table 3.5, the bounds increase to 16-66 percent for HA and 20-73 percent for GMI. There is also a substantial discrepancy between the lower and upper bounds for the rate of inclusion of the non-poor for both benefits. In Table 3.4, the estimates range between 32-38 percent for HA and 23-39 percent for GMI. These increase to 22-57 percent for HA and 17-56 percent for GMI in Table 3.5. The variation in the rates is also large for the leakage of HA and GMI in Table 3.5, 42-77 percent for HA and 41-80 percent for GMI; in contrast, in Table 3.4 it is only 60-66 percent for HA and 56-73 percent for GMI. However, the exclusion of the poor rate shows relatively close bounds for HA and GMI according to both tables.

The estimated bounds for CA are much narrower in Table 3.5 than in Table 3.4. Furthermore, the lower limit for the exclusion of the poor while being 0 percent in Table 3.4 is 18 percent in Table 3.5.

It should be stressed that the two tables show ranges based on the extreme assumption that benefit underreporting is the (only) reason why the number of benefit receipts in EU-SILC is lower than the number of entitlements calculated by EUROMOD and the number of benefit receipts from administrative data. Despite larger variations in some of the estimates for HA and GMI in Table 3.5 and CA in Table 3.4, we can see that the issues of targeting errors are persistent and suggest flaws in the benefit design and implementation.

3.4.4 Impact on poverty

Means-tested benefits are an important income source for the poor households, who receive them. In EU-SILC, for recipients in the poorest 10 percent of the population, GMI provides on average 67 percent of household disposable income, HA provides 46 percent, and CA 33 percent (all conditional on receipt). Across those in receipt of at least one benefit, the benefit share of household income is, on average, 51 percent for the bottom income decile group. These proportions fall quickly as income rises, although benefits remain a significant income source up to the third decile (or the fourth decile in the case of CA) for those receiving them.

Although an important income source for some of those in poverty, the benefits have a very small impact on reducing the poverty rates. Table 3.6 shows the estimated poverty figures based on the pre-transfer (column 2) and post-transfer (including reported benefits, column 3; or including simulated entitlements, column 5) equivalised household income. The effect of the transfers is measured by the Foster-Greer-Thorbecke (FGT) (1984) poverty indicators: poverty headcount, gap and severity. The headcount ratio is the share of people with equivalised income below the poverty line. The poverty gap is the per capita amount of money, as a percentage of the poverty line, needed to be transferred to the poor to be lifted above the poverty threshold. The poverty severity shows the poverty variation by taking the square of the poverty gap relative to the poverty line.

First, comparing pre-transfer and post-transfer estimates (columns 2 and 3 in Table 3.6): The poverty rate in 2007 based on the pre-transfer equivalised income is 18.1 percent, and the estimated reduction is only 0.1 percentage points (pp) (or 0.6 percent). The pre-transfer poverty gap is 6.3 percent (1.2 billion BGN). However, the total budget of the three means-tested benefits represents only 28 percent of the gap (Boshnakov et al., 2012), while the spending on all means-tested benefits provide 34 percent of the gap (Eurostat, 2014); thus, even assuming that all poor would be reached by the transfers, these programmes would reduce the gap by around one third. Due to large targeting errors found in the previous subsection, the estimated reduction in the poverty gap after the provision of the transfers is only 0.6pp (or about 9 percent).

We can compare these results with evidence for other European countries. Sainsbury and Morissens (2002) discuss the impact of means-tested benefits on poverty reduction across several European countries at the beginning and in the mid-90s. In the later period, the largest absolute poverty reduction effect is observed in the Czech Republic, Sweden, Finland, UK and Poland with absolute poverty reduction equal to 4.2pp, 5.5pp, 5.1pp, 8.5pp and 4pp, respectively. In Germany, the Netherlands, Hungary, France, Belgium and Italy, the effect is much smaller (2.7pp, 2.6pp, 1.8pp, 1.7pp, 0.8pp and 0.2pp, respectively), however, still larger than in Bulgaria.

Avram (2016) shows that the poverty reducing effect of social assistance in 2007 in the

Czech Republic, Hungary, Poland, Slovenia and Slovakia is also larger than in Bulgaria. These results can be explained by the much larger coverage of the programmes among the poor population and the larger spending as a share of the poverty gap. Furthermore, in the three Baltic countries, where both coverage and spending are smaller, the poverty reduction effect is still slightly larger than the one we observe in Bulgaria.

If we compare the pre-transfer with post-transfer poverty figures, based on the simulated benefits (columns 2 and 5 in Table 3.6), the simulated benefits reduce the headcount by 0.1pp (0.7 percent), and the gap and severity both by 1.4pp (22 percent and 43 percent, respectively). Importantly, the simulated results demonstrate that with error-free programme implementation the benefit payments would reduce the poverty gap and severity around 3 times as much as the observed benefits do. These findings suggest that there is scope for policy improvement. And yet, poverty rates do not change dramatically, showing that the generosity of the benefits is too low for them to contribute to a large poverty reduction.

[Table 3.6 here]

3.5 Reform scenarios

The findings on targeting errors and poverty reduction raise concerns about the effectiveness of the benefit programmes, and suggest the need to explore policy alternatives which could result in better targeting and higher poverty reduction. In this section we explore the poverty reducing effect of five different reform scenarios by using EUROMOD to calculate benefit entitlements under hypothetical policy rules. We assume full take-up and no leakage throughout.

The first reform, called the income-test reform, alters the income-test only, while leaving the rest of the policy rules the same, with the aim to improve targeting of the poor. The reformed income-test is based on equivalised household disposable income, instead of per capita gross family (CA) or household (HA and GMI) income, as embedded in the current legislation.

The remaining four reform scenarios illustrate the abolition of the three means-tested benefits and the introduction of only one benefit which will be equal either to a flat rate, or to the shortfall between the poverty threshold and the equivalised household disposable income. The arguments in favour of such reforms are that administering only one programme instead of three implies fewer costs to government agencies; simplifying and decreasing the number of eligibility criteria could lead to an increase in the take-up rate; better targeting of benefit resources towards the poor could increase the poverty reduction effect of the transfers.

A budget-neutral scenario would involve a flat rate of 12.7 BGN per month being given to individuals with equivalised household disposable income below the 60 percent of the median poverty line. The other three scenarios differ from each other in the definition of the poverty line: it is in turn 40 percent (40pl), 50 percent (50pl) or 60 percent (60pl) of the median equivalised household disposable income. In terms of total cost, the 40pl and income-test reforms will be cheaper than the existing systems, with a budget of 49 percent and 84 percent, respectively, of the budget for existing benefits. However, the number of benefit entitlements will be also significantly smaller, only 30 percent and 43 percent, respectively, of the number of the 2007 benefit recipients. The budget-neutral, flat-rate benefit will have nearly the same number of benefit entitlements, 89 percent. The other two scenarios, 50pl and 60pl suggest higher spending, equal to 1.03 and 1.96 times the 2007 budget. Both scenarios will provide fewer entitlements, 57 percent and 89 percent, respectively.

Table 3.7 shows that, under the cheapest scenario, the 40pl reform, the reduction in the poverty gap and severity (0.9pp (equal to 14 percent) and 1.1pp (equal to 32 percent), respectively) would be greater than by the observed in the EU-SILC 2007 benefits (but less than by the simulated entitlements). The next cheapest option, the income-test reform, would have a larger reduction effect on the rates (larger than by the observed benefits as well as simulated entitlements). After the changes, the benefits would reach more households below the poverty threshold and provide them with higher benefit amounts. As a result, the headcount would be reduced by 0.4pp (2 percent), and the poverty gap and severity both by 1.6pp (26 percent and 48 percent, respectively). These results highlight once again that the level of the benefits is too low and that there is potentially room for improvement.

The budget-neutral, flat rate reform would have much larger headcount reducing effect of 2.9pp (16 percent). The effect on both poverty gap and severity would be around 2-3 times higher than the effect of the 2007 observed benefits (although the effect on poverty severity will be lower compared to the effect of the simulated entitlements). Thus, at the same cost, policy effectiveness in terms of poverty reduction can be significantly increased.

The 50pl reform would have a larger effect on the gap and severity (1.8pp (equal to 28 percent) and 1.7pp (equal to 50 percent) reduction, respectively) but no effect on the headcount (the same as the 40pl reform). Finally, the 60pl reform would have the largest poverty reducing effect leading to the headcount, gap and severity falling by 3.4pp (19 percent), 3.1pp (50 percent) and 2.2pp (66 percent), respectively.[15]

[Table 3.7 here]

The results in this section are purely illustrative. By exploring five reform scenarios we show that there is a large scope for policy improvement which, if further explored, could contribute to better targeting of the benefits to those in need, more adequate income support, and a significant reduction in poverty.

3.6 Conclusion

In recent years, poverty has been increasing in Bulgaria, rising from 14 percent in 1999 to 21 percent in 2012. One of the explanations for this is the small impact that social transfers have on poverty, which could in turn partly reflect low levels of expenditures on social protection but may also be due to poor policy design or implementation.

We provide a comprehensive assessment of the performance of the three largest means-tested benefits in Bulgaria combining household survey data with estimates of entitlements to benefits produced by the tax-benefit microsimulation model EUROMOD. We measure their performance in terms of targeting by estimating rates of benefit non-take-up, leakage, exclusion of the poor, inclusion of the non-poor and the extent to which they reduce poverty. The paper contributes to the existing literature by providing some of the first

[15] It should be noted that poverty rates are not reduced by 100% because the definitions of the income-test and the equivalised income used for estimating the poverty indicators differ.

measures of non-take-up and leakage for an Eastern European country and of the benefits under study.

The analysis finds very high rates of non-take-up, leakage of the benefits to non-entitled households, exclusion of a large part of the poor, and inclusion of non-poor households and families mainly positioned in higher income deciles. Depending on the definition of benefit non-take-up, we find that more than 40 percent of the households entitled for HA and GMI do not claim the benefits. Although GMI is a benefit intended to have a widespread coverage of the population, due to the very low income-test and, possibly, due to stigma, it has the smallest number of entitled and, together with HA, the highest rate of non-take-up. In contrast, the child benefit CA, the entitlement to which is mainly defined based on the age of the children and a higher income-test, has a higher take-up, suggesting lower associated stigma with claiming the benefit or lower information costs.

Furthermore, a large proportion of the beneficiaries have incomes exceeding the income-test which should disqualify them from entitlement. This high rate of leakage could be explained by a failure of the social workers to administer the programmes correctly, by corruptions of civil servants through bribes or by under-declaring of claimants' incomes to the tax authorities. In either case, the very low performance of the benefits raises serious concerns about the quality of the programme implementation. We consider possible biases in the results that would arise if benefit receipt were underreported in EU-SILC, and calculate upper and lower bounds around the rates: the findings of the paper remain robust to these checks.

In addition, despite the objectives of the programmes to cover basic needs and provide income support to the vulnerable, the level of the benefits and the coverage of the poor population are too low to have a significant poverty-reducing effect.

Taking a longer-term perspective, since 2007, not much has been done in terms of reforming the Bulgarian means-tested benefit system. The main changes have been to income-thresholds and benefit levels although we should note that statutory indexation rules are missing and the increases have lagged growth in prices and/or earnings (see Boshnakov et al., 2012 and Boshnakov et al., 2014). Given that the three benefits form the bulk of the social security budget spent on the poor, and given the increase in poverty in Bulgaria over the last decade, the results show that there is a need for policy improvement. We consider five potential reform scenarios and show that, even without increasing spending, the government could achieve the provision of more adequate income support and a significant reduction in poverty.

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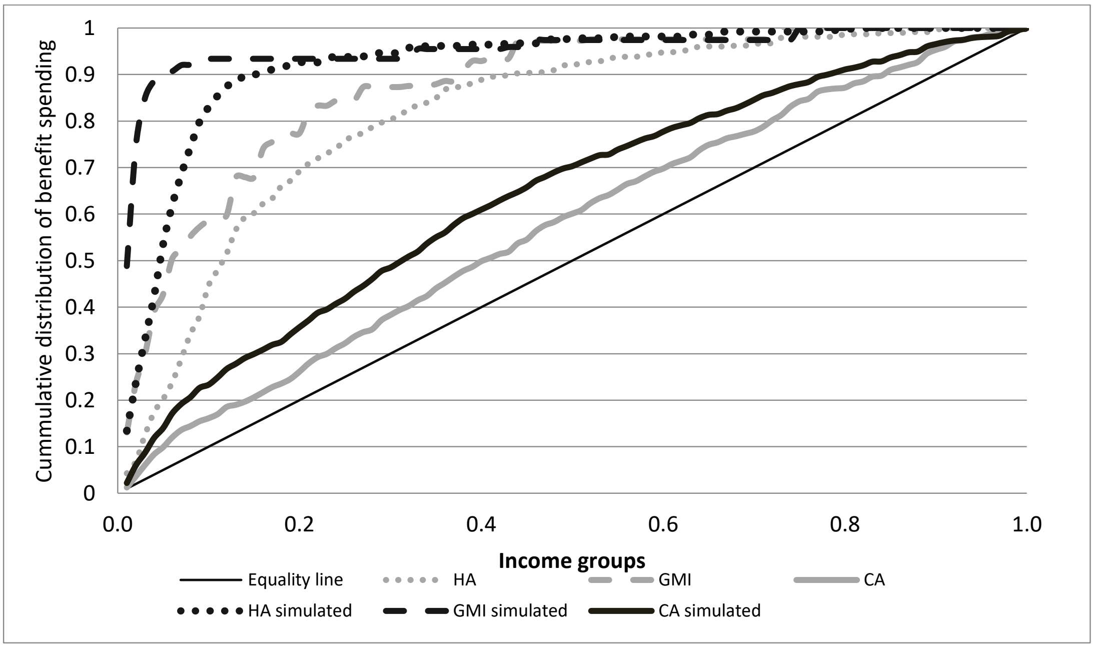
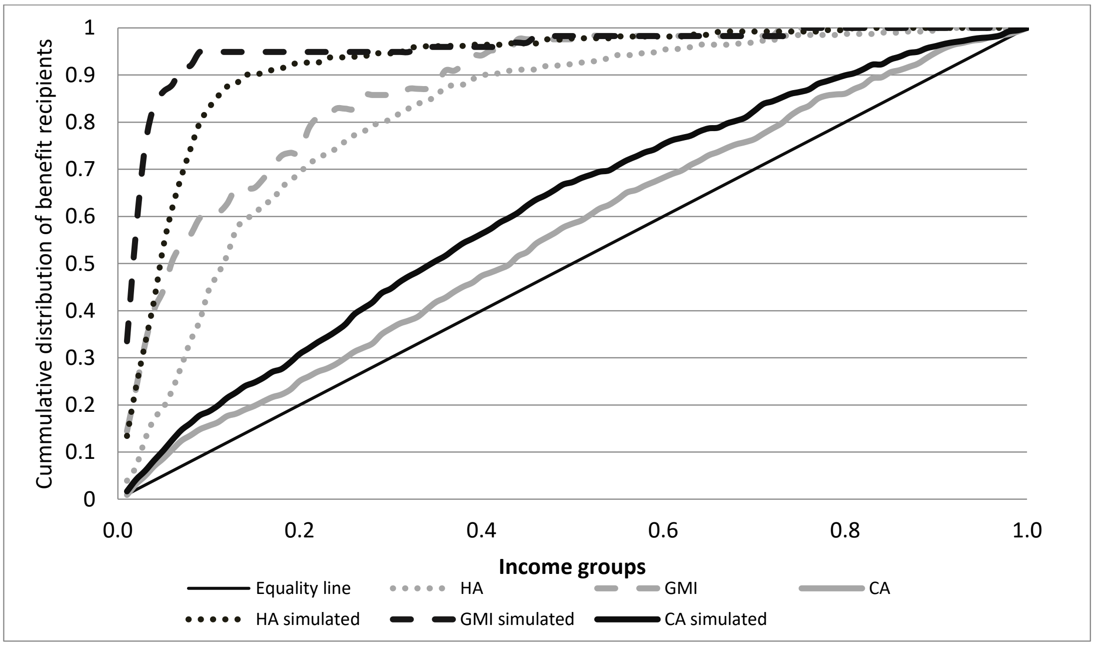
3.7 Figures

Figure 3.1: *Distribution of benefit spending over the income distribution*



Source: Authors calculations using EU-SILC 2008 and EUROMOD. *Notes:* The income distribution is based on equivalised household incomes before receiving each one of the transfers in turn. The unit of analysis is the household.

Figure 3.2: *Distribution of benefit recipients over the income distribution*



Source: Authors calculations using EU-SILC 2008 and EUROMOD. *Notes:* The income distribution is based on equivalised household incomes before receiving each one of the transfers in turn. The unit of analysis is the household.

3.8 Tables

Table 3.1:
A comparison between EUROMOD, administrative figures and EU-SILC

	EUROMOD (1)	Admin figures (2)	Ratio (1/2)	EU-SILC (4)	Ratio (4/2)
A. NUMBER OF SIMULATED BENEFIT ENTITLEMENTS/REPORTED RECIPIENTS (IN THOUSANDS)					
HA	208	300	0.69	195	0.65
GMI	56	77	0.73	46	0.60
CA	927	835	1.11	808	0.97
B. TOTAL SPENDING (IN MILLION BGN)					
HA	47	83	0.56	39	0.47
GMI	57	66	0.87	35	0.53
CA	206	193	1.07	140	0.73

Source: EUROMOD: Authors calculations using EUROMOD. Administrative figures: Boshnakov et al. (2012). EU-SILC: EU-SILC 2008 for Bulgaria.
Notes: EUROMOD number of simulated entitlements and EU-SILC number of recipients refer to households (GMA and HA) or children (CA). In the administrative figure, the number of GMI recipients equals the monthly-average number of recipients. The administrative figure for HA shows the total number of paid benefits, while for CA it refers to the number of children receiving the benefit. EUROMOD and EU-SILC figures are weighted.

Table 3.2:
Value of benefit entitlement for those entitled to and in receipt of the benefits

	HA	GMI	CA
Mean value of benefit:			
Reported	17	63	24
Simulated for those simulated eligible + reporting a positive amount	19	121	33
Simulated for those simulated eligible + *not* reporting a positive amount	19	72	25
Sample size:			
Reported	364	71	774
Simulated for those simulated eligible + reporting a positive amount	119	23	587
Simulated for those simulated eligible + *not* reporting a positive amount	238	76	290

Source: Authors calculations using EU-SILC 2008 and EUROMOD.
Notes: All rates are calculated at the household level. The mean benefit value is in the local currency, BGN. The reported benefits are taken from the EU-SILC data while eligibility and size of benefit entitlements (claimed and unclaimed) are simulated by EUROMOD.

Table 3.3:
Targeting error rates

Benefit	Indicator	Rates	Standard error	95% conf. interval	
				2.5%	97.5%
HA	Non-take-up 1	66.4	3.0	60.6	72.2
	Non-take-up 2	41.4	2.3	37.0	45.9
	Leakage	64.2	3.1	58.2	70.2
	Exclusion of the poor	77.3	1.5	74.4	80.1
	Inclusion of the non-poor	33.9	2.9	28.1	39.6
GMI	Non-take-up 1	73.2	5.4	62.6	83.8
	Non-take-up 2	46.9	4.8	37.4	56.4
	Leakage	67.6	6.4	55.2	80.1
	Exclusion of the poor	94.0	1.0	92.2	95.9
	Inclusion of the non-poor	27.1	5.9	15.6	38.7
CA	Non-take-up 1	38.8	1.8	35.2	42.4
	Non-take-up 2	33.9	1.7	30.6	37.1
	Leakage	19.4	1.7	16.0	22.8
	Exclusion of the poor	30.0	3.4	23.5	36.6
	Inclusion of the non-poor	77.9	1.7	74.5	81.2

Source: Authors calculations using EU-SILC 2008 and EUROMOD.
Notes: All rates are calculated at the household level. Bootstrap procedure has been used to calculate the standard errors and confidence intervals. The bootstrap is based on 1,000 replications of the total household sample.

Table 3.4:
Targeting error rates adjusted for benefit underreporting – based on a comparison between EU-SILC and EUROMOD

	HA			**GMI**			**CA**		
	baseline estimate	lower bound	upper bound	baseline estimate	lower bound	upper bound	baseline estimate	lower bound	upper bound
Imputations: non-recipients		entitled	non-entitled		entitled	non-entitled		entitled	non-entitled
Non-take-up 1	66.4	60.3	66.4	73.2	56.4	73.2	38.8	24.7	38.8
Non-take-up 2	41.4	37.6	*39.9*	46.9	36.1	*42.4*	33.9	21.5	*30.1*
Leakage	64.2	60.3	66.4	67.6	56.2	73.1	19.4	16.3	32.2
Imputations: non-recipients		poor	non-poor		poor	non-poor		poor	non-poor
Exclusion of the poor	77.3	74.9	77.3	94.0	92.4	94.0	30.0	0	30.0
Inclusion of the non-poor	33.9	31.7	37.9	27.1	22.5	39.4	77.9	71.1	89.1

Source: Authors calculations using EU-SILC 2008 and EUROMOD.
Notes: All rates are calculated at the household level.

Table 3.5:

Targeting error rates adjusted for benefit underreporting – based on a comparison between EU-SILC and administrative figures

	HA			**GMI**			**CA**		
	baseline estimate	lower bound	upper bound	baseline estimate	lower bound	upper bound	baseline estimate	lower bound	upper bound
Imputations: non-recipients		entitled	non-entitled		entitled	non-entitled		entitled	non-entitled
Non-take-up 1	66.4	16.2	66.4	73.2	20.4	73.2	38.8	35.6	38.8
Non-take-up 2	41.4	10.1	*31.5*	46.9	13.1	*35.0*	33.9	31.0	*32.9*
Leakage	64.2	41.8	76.7	67.6	41.3	80.3	19.4	18.6	22.8
Imputations: non-recipients		poor	non-poor		poor	non-poor		poor	non-poor
Exclusion of the poor	77.3	58.9	77.3	94.0	88.8	94.0	30.0	17.9	30.0
Inclusion of the non-poor	33.9	22.1	56.9	27.1	16.5	55.7	77.9	75.0	81.0

Source: Authors calculations using EU-SILC 2008 and EUROMOD.
Notes: All rates are calculated at the household level.

Table 3.6:

FGT poverty figures (in %) (change in percentage points (pp))

		Post-transfer			
Poverty indicator	Pre-transfer	Observed benefits	Change in pp	Simulated benefits	Change in pp
Headcount	18.10	17.99	-0.12	17.98	-0.13**
Gap	6.31	5.74	-0.58***	4.95	-1.37***
Severity	3.34	2.79	-0.55***	1.90	-1.44***

Source: Authors calculations using EU-SILC 2008 and EUROMOD.
Notes: The poverty line is equal to 60% of the median equivalised household disposable income in each scenario. $*\ p < 0.1$, $**\ p < 0.05$, $***p < 0.01$

Table 3.7:

FGT poverty figures (in %) under different reform scenarios (change in percentage points (pp))

		Post-transfer									
Poverty indicator	Pre-transfer	Income-test	Change in pp	Budget-neutral, flat rate	Change in pp	40pl	Change in pp	50pl	Change in pp	60pl	Change in pp
Headcount	18.10	17.75	-0.35***	15.25	-2.86***	18.10	0	18.10	0	14.68	-3.43***
Gap	6.31	4.69	-1.62***	4.69	-1.63***	5.44	-0.88***	4.56	-1.75***	3.18	-3.13***
Severity	3.34	1.73	-1.61***	2.21	-1.13***	2.28	-1.05***	1.67	-1.67***	1.13	-2.20***

Source: Authors calculations using EU-SILC 2008 and EUROMOD.
Notes: The poverty line is equal to 60% of the median equivalised household disposable income in each scenario. $*\ p < 0.1$, $**\ p < 0.05$, $***p < 0.01$

3.9 Appendix 1

Appendix 1 describes in detail the characteristics of the underlying household survey data from the European Union Survey on Income and Living Conditions (EU-SILC). The response rate of the EU-SILC survey is 66.6%. Household non-response is mainly due to the following three reasons. First, 7.3% of the households did not respond because e.g. it was not possible to contact them at their address. Second, 26% of the households that were contacted did not complete the interview due to refusal to cooperate, absence of household members or entire household, objective inability to respond, etc. Furthermore, due to person's non-response and inability to impute the missing data, 5 households were dropped from the sample. Children born after the income reference period were also excluded. The final sample size consists of 4,339 households represented by 12,148 individuals.

The National Statistical Institute (NSI) in Bulgaria, responsible for the collection of the data, has carried out various data cleaning and imputation procedures in case of income misreporting and unit non-response. For example, all gross income values have been checked against their net values. Lower and upper bounds based upon the national legislation have been also used as a check on most of the recorded social benefits and pensions. Administrative data from the National Social Security Institute, other administrative sources and data from previous waves of the longitudinal EU-SILC have been used for a comparison against extreme income values.

An example of the checks carried out by the NSI is in regard to the contributory family-related benefits. If an individual receives such benefits she is generally not eligible for non-contributory social assistance benefits. NSI checks for consistency and makes data adjustments accordingly. Other adjustments are carried out if reported benefit amounts exceed the maximum possible payments, e.g. in the case of benefits for unemployment, old-age, survivor, sickness and disability benefits. The data have also been corrected for possible double-reporting of income components.

In regard to the two social assistance benefits, HA (Q30.1) and GMI (Q30.3), the question asked in the household EU-SILC questionnaire is: 'Q.30 Have you or another member of the household received some of the following social benefits during 2007 for: Q30.1 assistance payments for heating; Q30.2 monthly assistance payments for rent; Q30.3 monthly monetary benefit for low income, Q30.4 lump-sum social aid for satisfying accidentally occurred health, educational, communal, household and other needs.' The respondent has to give answers for each of the benefits. If in receipt of the benefit, the respondent has to provide information on the duration of receipt and benefit amount.

For the CA (Q32.3), the question in the survey is: 'Q32 Have you or another member of the household received some of the following monthly family/children benefits during 2007 for: Q32.1 monthly benefits for bringing up a child younger than 1; Q32.2 monthly benefit for bringing up child with permanent disabilities; Q32.3 monthly child benefits till 18 years of age; Q32.4 monthly child benefits till 20 years of age with permanent disability'. Here as well, the respondent has to give answer on the duration and amount of each of the benefits.

The three benefits in the analysis are among the largest and most popular means-tested benefits in Bulgaria and their names are distinctive from each other suggesting they target different types of needs (provision of minimum income level, cash support for heating and support for children). Therefore, we do not have any reason to believe that respondents might not be aware of the name of the benefit if they receive it or that they have misreported it under a different benefit.

In terms of validating the income variables reported in EU-SILC, we did extensive checks as part of validating the entitlements simulations done by EUROMOD. We compared information on market incomes, benefits, pensions and taxes and social insurance contributions (number of recipients/contributors and aggregate amounts) with data from national accounts, Household Budget Survey estimates, and administrative data from the National Social Security Institute and Agency for Social Assistance. Where there were deviations between EU-SILC reported data, EUROMOD simulation results and data from external sources, these were carefully studied and explained by Boshnakov et al. (2012).

For employment income, Boshnakov et al. (2012) report that EU-SILC, relative to national accounts data, overestimates both the number of individuals with employment income (by 32.5 percentage points) and the total employment income (by 13.9 percentage points) which they explain could be due to informal employment and wages not accounted for in the national accounts. The average employment income in the survey is, however, 14.1 percentage points lower than the national accounts average which could be explained by the extra employees in EU-SILC reporting low amounts of income on average (this could reflect informal earnings or underreporting of amounts in EU-SILC; there is no evidence of the relative size of either issue).

For self-employment income, there are discrepancies between the definition of self-employed in EU-SILC and the one in the national accounts data which makes the comparison between the two sources problematic. Nevertheless, a comparison between the two sources shows the following: The number of self-employed in EU-SILC is exactly half the number reported in national accounts (see Boshnakov et al., 2012). The national accounts data for the total amount of self-employment income is captured in the category 'Net operating surplus and net mixed income' for the households. The total amount of self-employment income reported by respondents in EU-SILC is only 32.5% of the figure on 'Net operating surplus and net mixed income' from the national accounts data (see here: `http://nsi.bg/en/content/5547/annual-data`). For rent, the national accounts figure which captures officially declared rents shows a very small amount compared to the one reported in EU-SILC.

Public pensions and other benefits that enter the income-test for the three benefits studied in the paper seem to be well captured by EU-SILC. For more detailed information on EU-SILC data and EUROMOD simulations, see Boshnakov et al. (2012).

To sum up, we find limited evidence on the extent of income underreporting in EU-SILC and among the recipients of HA, GMI and CA. This does not allow us to measure the direction or size of a potential bias in the results.

3.10 Appendix 2

To explore the possibility that our results on non-take-up and leakage can be explained by measurement error in the income data, we performed a simulation. As Hernandez and Pudney (2007) argue, estimating jointly the extent of measurement error and non-take-up based purely on data on incomes that contains measurement error is very challenging. Nevertheless, we present the results for illustrative purposes.

First, we simulated income data which is log-normally distributed and identical in their statistical moments (mean and variance by income centiles) to the income data observed in EU-SILC and based on which benefit entitlements are assessed. As this exercise is for illustrative purposes we assumed that the simulated income data represent true incomes as opposed to the EU-SILC data which contain measurement error. Second, as the targeting measures are assessed at the household level, the number of observations in the simulated data equals the number of households in EU-SILC. Third, we simulated entitlement to the three benefits HA, GMI and CA assuming full take-up and no leakage. We added to the (log of the) simulated income data a random term with a mean of 0 which is normally distributed. In summary, the simulations show that such type of measurement error does not seem to generate a pattern of income misreporting that would explain the results in the paper. Specifically, we assumed different values for the standard deviation of the random term which showed the following results, also reported in Table A2: A random term with standard deviation of 0.35 would re-produce (almost) the same non-take-up rate based on the second definition for HA and leakage rate for CA observed in the paper. The generated non-take-up rate based on the first definition for HA, non-take-up rates (both definitions) for GMI and CA as well as leakage rates for HA and GMI would be lower than the ones estimated in the paper. Notably, the standard deviation of the income will be increased by a substantial 22 percent.

Increasing the standard deviation of the random term to 0.4 would result in an even larger 29 percent increase in the standard deviation of the income data. The simulations show that the non-take-up rate based on the second definition for HA and the leakage rate for CA will be slightly overestimated. The non-take-up rate based on the second definition for GMI will be re-produced at a level as estimated in the paper. However, the non-take-up rates based on the first definition for HA and GMI and both definitions for CA will continue to be underestimated. The leakage rates for HA and GMI will be still nowhere near the rates estimated in the paper.

Introducing a random term with standard deviation of 0.6 would add a lot of noise to the income data a 70 percent increase in the standard deviation. The simulations show that the leakage rate for CA and the non-take-up rates based on the second definition for HA and GMI will be overestimated. However, adding the random term to the income data will generate almost the same non-take-up rates based on the first definition for HA and GMI as the ones estimated in the paper. The non-take-up rates for CA and leakage rates for HA and GMI will yet not be achieved by this simulation.

The non-take-up rates for CA would be about the same as in the paper if the random term has a standard deviation of 1.2. However, this will also result in 6 times increase in the standard deviation of the income data.

The leakage rates for HA and GMI estimated in the paper cannot be achieved by any plausible value of the standard deviation of the random term (as we increase the standard deviation, leakage rates for both benefits converge to around 50%, which is about 20-30 percent lower than the rates estimated in the paper).

Table 3.8:

Comparison between non-take-up and leakage rates estimated in the paper and from a simulation exercise

		Estimates in the paper (EIP)	Simulation results after adding a random term to the income data									
			SD=0.35	Proportion of EIP	SD=0.4	Proportion of EIP	SD=0.6	Proportion of EIP	SD=1.2	Proportion of EIP	SD=1,000,000,000	Proportion of EIP
HA	Non-take-up 1	66.4	47.7	0.7	52.3	0.8	65.5	1.0	80.0	1.2	90.8	1.4
	Non-take-up 2	41.4	40.6	1.0	44.6	1.1	56.6	1.4	71.2	1.7	83.0	2.0
	Leakage	64.2	24.8	0.4	26.4	0.4	31.0	0.5	38.1	0.6	50.1	0.8
GMI	Non-take-up 1	73.2	45.4	0.6	52.1	0.7	71.6	1.0	90.2	1.2	97.9	1.3
	Non-take-up 2	46.9	40.9	0.9	47.2	1.0	65.8	1.4	85.8	1.8	95.6	2.0
	Leakage	67.6	16.1	0.2	17.7	0.3	23.3	0.3	33.5	0.5	50.0	0.7
CA	Non-take-up 1	38.8	19.8	0.5	22.3	0.6	30.9	0.8	46.1	1.2	65.6	1.7
	Non-take-up 2	33.9	16.5	0.5	18.3	0.5	24.3	0.7	34.7	1.0	48.6	1.4
	Leakage	19.4	19.5	1.0	21.6	1.1	28.2	1.5	37.5	1.9	50.0	2.6

Source: Authors calculations. *Notes:* The random term is assumed to have a zero mean and to be normally distributed. SD stands for the standard deviation of the random term. The cells are highlighted in grey if the non-take-up and leakage rates from the simulation exercise are equal or higher than the rates estimated in the paper. The simulations are based on 1,000 replications.

Chapter 4

Improving Poverty Reduction in Europe: What Works Best Where?[1]

(published in 2018 in the Journal of European Social Policy and co-authored with Chrysa Leventi and Holly Sutherland)

Abstract

This paper examines how income poverty is affected by changes to the scale of tax-benefit policies and which are the most cost-effective policies in reducing poverty or limiting its increase in seven diverse EU countries. We do that by measuring the implications of increasing/reducing the scale of each policy instrument, using microsimulation methods while holding constant the policy design and national context. We consider commonly-applied policy instruments with a direct effect on household income: child benefits, social assistance, income tax lower thresholds and a benchmark case of re-scaling the whole tax-benefit system. We find that the assessment of the most cost-effective instrument may depend on the measure of poverty used and the direction and scale of the change. Nevertheless, our results indicate that the options that reduce poverty most cost-effectively in most countries are increasing child benefits and social assistance while reducing the former is a particularly poverty-increasing way of making budgetary cuts.

[1]Acknowledgements: The authors are grateful to Bea Cantillon, Francesco Figari, Tim Goedemé, John Hills, Alari Paulus and István Tóth, two referees and the Editor for valuable comments and suggestions. The version of EUROMOD used in this paper is G2.34 together with micro-data from the EU Statistics on Incomes and Living Conditions (EU-SILC) made available by Eurostat (59/2013-EU-SILC-LFS). For Estonia and Greece national variables are also used, provided by the respective national statistical offices; for Italy the national EU-SILC data made available by ISTAT are used; and for the UK Family Resources Survey data are made available by the Department for Work and Pensions via the UK Data Service. The usual disclaimers apply. The research in this paper was financially supported by the European Union Seventh Framework Programme under grant agreement n 290613 (ImPRovE project). The authors also acknowledge support from the ESRC Research Centre for Micro-Social Change (MiSoC) at the University of Essex.

Keywords: poverty, EU, social and fiscal policy, policy reform, microsimulation

JEL codes: D13, D30, H53, I38

4.1 Introduction

With its roots in the late nineteenth century, the modern welfare state is now established in all European Union (EU) member states. One of its most important missions has become poverty reduction. While combating poverty is a high priority objective in the EU, income poverty remains persistently high or is rising in many European countries and the EU2020 targets for poverty reduction seem unattainable (Eurostat, 2017b). It is clear that, in order to move towards the targets in a convincing way, there is need for increased and differently-allocated public spending. However, in the context of the recovery from the economic crisis, or its persistence in some countries, budgetary retrenchment remains on the agenda.

Research on public redistribution has focused on tax-benefit policies, as the main tools through which governments influence distributional outcomes. The effectiveness of policies in reducing poverty depends on a number of factors. First, the environment in which they operate plays a key role. This applies first to the characteristics of the population for whom they are intended and the macroeconomic conditions of the time (Atkinson, 2009). Second, the effectiveness of particular policy instruments naturally depends on the specifics of their design (Levy et al., 2009; Avram et al., 2013). Third, it depends on how people react to policies. For example, targeting resources on those with low incomes may appear efficient for poverty reduction but is less so if means-testing results in incomplete benefit take-up or if benefits reduce the financial incentive to work for the recipients or others in their household (Adema et al., 2003; Mood, 2006; Bargain et al., 2007). Finally, effectiveness in reducing poverty depends on the scale of the policy instrument.

Research on how much 'size matters' relative to design has mainly concentrated on family policies (e.g. Matsaganis et al. (2006) for southern European countries, Levy et al. (2007) for Austria, Spain and the UK, Notten and Gassmann (2008) for Russia, Salanauskaite and Verbist (2013) for Lithuania and four other post-2004 EU member states, and Popova (2016) for Russia in comparison with four western European countries). Most findings suggest that size is the most important aspect but that specific design features may be particularly effective in poverty reduction within their national contexts.

The questions we attempt to answer in this paper are the following: how are income poverty levels affected by changes to the scale of tax-benefit policies? Which are the most cost-effective policies in reducing poverty in seven diverse EU countries? With these questions in mind, we address two important limitations of the existing literature: first, while the literature mainly focuses on one type of policy (family benefits), our analysis compares across several types of policy instruments within as well as between countries. The policies considered are child benefits, social assistance benefits and income tax lower thresholds. In addition, to provide a benchmark against which to compare the effects of individual policy instruments, we consider what happens to poverty indicators if all monetary levels and thresholds in the tax-benefit system are altered. Second, while most of the literature concentrates on the poverty-reducing effectiveness of different policy designs, this research sheds light on the effectiveness of the scale of given policy designs; using microsimulation techniques, we explicitly measure the distributional implications of increasing or reducing the scale of each policy, holding constant its design and national context.

To assess the relative cost-effectiveness of the instruments in reducing poverty, we also contribute to the existing literature by developing an indicator, defined as the ratio of the percentage point change in poverty (headcount or gap) to the net cost to the public budget, expressed as a proportion of GDP.[2] This indicator allows us to compare the cost-effectiveness across instruments and countries in a meaningful and straightforward way.

We compare across seven EU countries chosen for their diversity of tax-benefit systems and size of policy instruments: Belgium, Bulgaria, Estonia, Greece, Hungary, Italy and the UK. These countries cover the whole spectrum of European non-pension social spending: from the high spenders (Belgium and the United Kingdom with 19.1% and 16.1% of GDP in 2013, respectively) to the low spenders (Bulgaria and Estonia with 9.4% and 8.2% of GDP in 2013, respectively).[3] Average levels also differ substantially: the mean value of child benefits (for those in receipt) varies from 6% of the median equivalent disposable income in Greece to 27.5% in Hungary. Large variations are also observed for social

[2]This is closely related to measures of target efficiency developed by Beckerman (1979).
[3]See Eurostat (2017a), indicator spr_exp_sum.

assistance benefit levels and the income levels at which people become liable for income tax (Table 4.1). This diversity is important, as it enables us to compare a number of different policy settings and, hence, reach conclusions that go beyond the seven countries in question on top of providing country-specific pointers for practical policy reform.

We use EUROMOD, the tax-benefit microsimulation model for the European Union and household micro-data, representative of the national populations. Combining EUROMOD with the micro-data provides a unique opportunity to experiment with the scale of the instruments for a wide range of increases and decreases. It also allows us to calculate with precision and cross-country comparability the net effects of policy changes, taking into account the complex interactions within and between the tax-benefit policies as well as the heterogeneity of population characteristics.

The paper is structured as follows: Section 4.2 describes the rationale for choosing the policy instruments and explains how they are scaled up and down. Section 4.3 explains the methodology that is used. Section 4.4 presents our estimates of the effect of changes to each of the policy instruments on poverty and compares cost-effectiveness across countries and instruments. The final Section 4.5 concludes by summarising the most important findings and by reflecting on the policy implications of this analysis.

4.2 The policy instruments

The instruments we focus on have been chosen on the basis of two criteria. First, they are commonly considered as components of reform strategies to reduce income poverty (or restrain its growth). Thus, we analyse non-contributory benefits that either aim to target the poor or provide universal support rather than contributory benefits which have insurance against risks (e.g. unemployment) as their primary aim. Second, the instruments already exist in most EU countries, and hence are suitable for consideration in a comparative context.

[place Table 4.1 here]

We consider how cost-effectiveness depends on the scale of the instrument by expanding/contracting relevant monetary levels and thresholds by common percentages: 5%, 20%, 50%, 70% and 90%.[4] We also disentangle the part of poverty change that is related to changes in eligibility (that is, fewer/more benefit recipients/tax payers) and the part related to changes in benefit/tax threshold levels for those already in receipt/liable.

4.2.1 Child benefits

We expect increasing the scale of child benefits to contribute to reducing poverty among households with children. The extent of the effect depends on the design of the benefit, whether or not benefit entitlements depend on the age and number of children, and how they impact on the particular households with children below the poverty line (Bradshaw, 2006). If the benefit is universal it may appear to be less cost-effective in terms of poverty reduction than a benefit targeted on low income families, but it will have the advantages of high take-up and political support (Matsaganis et al., 2006; Notten and Gassmann, 2008; Levy et al., 2013).

We focus on non-contributory cash benefits specifically targeted at children. Per-child and per-family amounts in universal and means-tested child benefits are adjusted.[5] We also adjust income thresholds in any child benefit means tests, so the number of beneficiaries changes. We do not adjust maternity and parental benefits or child-contingent components of adult out-of-work/in-work or housing benefits, nor support for children channelled through the personal income tax system, which is considerable in Hungary.[6]

For the instruments we consider, Table 4.1 shows how the average value compares with median equivalised household disposable income and the proportion of all households relying on the instrument (in the case of benefits only) in each country. Child benefits are

[4]We choose not to show the effects of abolishing instruments entirely because in some policy systems receipt of a particular benefit acts as a passport to entitlement to other benefits or as an alternative to receipt of other benefits. Invoking these effects would distract from our focus on the effectiveness of particular instruments.

[5]The benefits that are adjusted here are as follows: **Belgium**, non-means-tested child allowance, means-tested child allowance; **Bulgaria**: means-tested child benefit, non-means-tested birth grant, non-means-tested child benefit for mothers in tertiary education, means-tested child benefit for education, non-means-tested benefit for twins; **Estonia**: child allowance, childcare allowance, parental allowance for families with 7+ children, childbirth allowance, foster care allowance (all non-means-tested); **Greece**: child benefit, large family benefit (both means-tested); **Italy**: means-tested family allowances for lone parents, two parents and for families with at least 3 children; **Hungary**: non-means-tested family allowance, means-tested regular child protection benefit, non-means-tested maternity grant, non-means-tested child raising support, non-means-tested child care allowance; **UK**: means-tested child tax credit, non-means-tested child benefit.

[6]Figari et al. (2011) analyse the impact of the whole package of child contingent incomes.

relatively generous in Hungary, the UK and to a lesser extent in Belgium. They are much more modest in Greece, Estonia, Italy and Bulgaria. In the latter group of countries only a minority of households with children is entitled to such benefits.

4.2.2 Social Assistance

Expanding the generosity of cash social assistance schemes is an effective way of increasing the income of existing recipients, and may also draw in more people who have incomes that previously made them ineligible. However, the poverty effect of increasing the social assistance level depends not only on the level relative to the poverty threshold and if conditions of entitlement exclude some people by design (Figari et al., 2013; Van Mechelen and Marchal, 2013) but also on non-take-up of the benefits due to stigma, mis-administration or other reasons (Eurfound, 2015).

Table 4.1 shows that Belgium is the country with the highest average benefit payment and the second lowest benefit prevalence among the seven. The UK comes second in terms of average payment and first in terms of prevalence.[7] In Hungary the prevalence is very low and no national cash social assistance benefits were available in Greece and Italy in 2013.[8]

4.2.3 Income tax threshold

Raising the income level at which people become liable for income tax is a way of increasing their disposable income that could in principle take them out of poverty or reduce the poverty gap. However, this depends on the relationship between the tax and poverty thresholds. If the tax threshold is already high there may be few people in poor households who are liable for income tax.

Bulgaria and Hungary are not included in this part of the analysis as they have a flat tax without an income-exemption limit. In Italy, where tax credits operate instead of income exemptions, the amounts of these tax credits are increased/decreased instead. In

[7]The specific benefits that are included are: **Belgium**: income support, **Bulgaria**: guaranteed minimum income, heating allowance; **Estonia**: subsistence benefit, means-tested subsistence benefit for families; **Hungary**: social assistance (regular benefit and stand-by allowance); **UK**: income support, income-based jobseeker's allowance, pension credit. All benefits are means-tested.

[8]See World Bank (2015) and Ravagli (2015), respectively, for analysis of the effects of potential schemes in these two countries.

Greece, in 2013 there was no zero-rate band or equivalent but the system of 2012 (and all the previous ones) included this component. Our simulations first re-introduce that and then explore the effect of amending it.

Table 4.1 shows that the threshold varies greatly: in Estonia it is half the size of that in Greece, Italy and the UK.

4.2.4 Re-scaling the whole tax-benefit system

To provide a benchmark against which to compare the effects of individual policy instruments, we consider what happens to poverty indicators if all monetary levels and thresholds in the systems of direct taxes and cash benefits are increased/decreased. One might expect comprehensive whole-system changes to be less closely targeted on low income households than some of the individual policy instruments that we consider. The effect depends on the salience of monetary levels, amounts and thresholds in the tax-benefit system and where in the income distribution these thresholds apply.[9] It may therefore differ across countries and our analysis throws some light on this issue.

4.3 Methodology and data

4.3.1 Model, data and assumptions

We use the tax-benefit microsimulation model EUROMOD and household micro-data on gross incomes, labour market status and other characteristics of individuals and households. Intuitively, EUROMOD does the following: first, country-specific tax and benefit rules (as at 30 June 2013 in our analysis) are applied to the household data. By doing so, EUROMOD identifies in the data i) who (e.g. individual or family) is entitled to receive a benefit or is liable to pay income taxes or social insurance contributions (SIC) and ii) how much the benefit entitlements and tax or SIC liabilities amount to. Second, a measure of cash household net income is derived based on the sum of the reported gross incomes and the calculated benefit entitlements, net of taxes and SIC.

[9] For related analysis on the UK see Sutherland et al. (2008) and on the same 7 countries, Hills et al. (2014).

Using EUROMOD combined with household data is crucial in our analysis for the following reasons: we can simulate changes to the parameters of policies, by taking into account all resulting changes to both the eligibility and the level of benefit/tax amounts at the individual/household level. In turn, this allows us to decompose the change in the poverty levels due to changes in the instrument size by changes in the population coverage versus the benefit/tax level. Furthermore, when changes to a particular instrument are simulated this may affect other benefit entitlements or tax liabilities. These interactions are taken into account as it is the net effect on household income that is relevant. Finally, both the model and household data have been harmonised across countries to allow for meaningful and consistent cross-country comparisons. EUROMOD has been validated both at the micro and macro level and has been extensively used to address a wide range of economic and social policy research questions (see Sutherland and Figari (2013) and Figari et al. (2015)).

The household data come from the 2010 European Union Statistics on Income and Living Conditions (EU-SILC) for Belgium, Bulgaria, Estonia, Greece, Italy and Hungary. For the UK, the 2009/10 Family Resources Survey (FRS) is used. Gross market incomes are updated from the micro-data income reference period (2009) to the target period (2013) using appropriate indices for each income source. Information on income components that cannot be calculated by EUROMOD is taken directly from the data and updated to 2013, along with market incomes.[10] No adjustments are made for economic or demographic changes in the period 2009-13.

Non-take-up of means-tested benefits is an important phenomenon to account for in evaluating their distributional impact. In the case of non-take-up of social assistance and means-tested child benefits, their poverty effect would be overestimated if full take-up were assumed. In EUROMOD we make adjustments for benefit non-take-up where there is relevant information: to social assistance benefits in Belgium and all means-tested benefits and tax credits in the UK (Leventi and Vujackov, 2016). We assume no change in take-up probability in the case of our simulated reforms and we do not attempt to capture behavioral reactions to policy changes in any dimension. Finally, the policy scenarios are

[10] Non-simulated components are typically contributory pensions and maternity benefits and disability benefits. They are not simulated because of insufficient information in the household micro-data about work history or disability status to calculate eligibility or size of entitlement.

not revenue-neutral by design, because the point is to measure the budgetary cost. Any financing mechanism would itself have distributional and behavioural effects.

4.3.2 Evaluating the results

We measure effectiveness of the policy instruments according to their impact on income poverty measured using a fixed threshold of 60% of the national median household disposable income in 2013. To account for household size and economies of scale within the household, household incomes are equivalised using the modified OECD scale (assigning a value of 1 to the household head, 0.5 to any other adult and 0.3 for each child aged under 14). We use the poverty headcount ratio (that is, the percentage of the population living below the poverty line) and the normalised poverty gap ratio (that is, the average poverty gap[11] expressed as a ratio of the poverty line).[12] We calculate standard errors for the results based on the DASP package developed by Araar and Duclos (2007), taking into account sampling variation.

We evaluate the change in poverty in relation to the change in the net budgetary cost to the public finances. We use as an indicator of cost-effectiveness the ratio of the percentage point change in poverty (headcount or gap) to the change in net budgetary cost (spending on cash benefits less revenue from direct taxes and SIC), expressed as a proportion of GDP. This provides a metric that can be compared across the policy instruments and across countries.

4.4 Results

The effects of changes to the three policy instruments on the poverty headcount and gap are discussed policy-by-policy and in relation to their budgetary implications (shown graphically in Figures 4.1 to 4.3), and also relative to re-scaling the whole systems (Figure 4.4). Detailed results for the 5%, 20%, 50%, 70% and 90% increases/decreases are shown in the Appendix (Tables 4.3, 4.4). Table 4.2 provides an assessment of the relative cost-effectiveness of the instruments within and across countries.

[11]Poverty gap is the mean shortfall of the total population from the poverty line (counting the non-poor as having zero shortfall), expressed as a percentage of the poverty line.

[12]These indicators correspond to FGT0 and FGT1 from Foster et al. (1984).

4.4.1 Child benefits

As shown in the Appendix (Tables 4.3 and 4.4), increasing child benefits by 20% has a modest effect on the poverty headcount, lowering it by 1.3 percentage points (pp) in the UK, 1.2pp in Hungary and 0.9pp in Belgium (the countries with the largest child benefit systems), but by much less in the other countries. An increase of 90% would result in a reduction of the headcount by at least 1pp in all countries, with large inroads in Hungary (4.8pp), the UK (3.5pp) and Belgium (3.3pp). The same three countries show the largest effects on the poverty gap.

Figure 4.1a shows that in many countries the effect on the poverty headcount is broadly proportional to the scale of the change in spending on child benefits (measured in terms of percent of GDP), both for increases and decreases: the lines are straight and the effects are symmetrical for increases and decreases. There are some exceptions as well as differences in the gradient of the effects (that is, differences in poverty effectiveness depending on the scale of the benefit). The poverty rate falls fastest for a given increase in child benefit spending in Hungary and rises fastest for a given reduction in spending in the UK.

These differences can be explained by a number of factors: the density and composition of populations affected by the changes in benefits, the relationship between any income thresholds and the poverty threshold, and the nature of the benefit designs. There are some interactions with other parts of the tax-benefit system: in Hungary elements of the child benefit are taxable and in Bulgaria, Estonia and Hungary they are included in the assessment for social assistance entitlement and for housing benefit in the UK. But these do not seem to play a major role in explaining the differences in patterns of cost-effectiveness, since in many cases they affect both the budgetary effect and the income position of the household relative to the poverty threshold.

For example, the UK is distinguished by a generous means-tested child benefit, on top of a child benefit that is not means-tested except at high incomes. Together they bring many families from below to above the poverty threshold and further expanding them is not only increasingly less cost-effective because fewer recipients are poor, but also costs increase due to extension of coverage of the means-tested component as well as the level of both benefits for existing recipients. Reductions in size have a proportionately large adverse effect on poverty because many benefit recipients are brought from above to below the poverty threshold in part due to reductions in coverage. A similar reduction in cost-effectiveness is observed in Belgium for high levels of expansion, because of increasing proportions of recipients of the mainly non-means-tested benefit having crossed above the poverty threshold. Stronger effects in the other direction, as in the UK, are not observed as coverage effects are minimal in the mainly universal Belgian child benefit system. In Hungary, the other country with large child benefits, mostly universal, cost-effectiveness is broadly unrelated to scale.

In the case of Bulgaria, the reduction in spending is smaller for larger reductions in child benefits, that is, the rate of return is decreasing. This is mostly due to the population composition; there are fewer families with very low incomes (between 10% and 30% of the value of the child benefit income-test) than with low incomes (between 30% and 50% of the value of the child benefit income-test). It is also due to the interaction between child benefits and social assistance; spending on social assistance benefits increases when scaling down child benefits but income levels on social assistance are too low for there to be an effect on the poverty headcount.

Figure 4.1b shows the relationship between child benefit spending and the poverty gap, which is still linear for the four countries with smaller child benefits, with Estonia showing somewhat lower poverty effectiveness (smaller gradient) than Bulgaria, Greece or Italy. This suggests that the relatively small benefits are important for reducing the poverty gap, but even the 90% increase does not succeed in lifting many households above the poverty threshold. The relationships are not linear in Belgium, Hungary or the UK with higher poverty gap reduction effectiveness at lower levels of spending. This can be explained by larger benefits lifting households above the poverty threshold, where they no longer contribute to the poverty gap. This flattening of the curve at higher spending levels is particularly evident for the UK where increasing child benefits by 90% would imply a poverty gap reduction of less than one fifth, whereas reducing benefits by 90% would imply an increase in poverty gap of 70%. For these three countries over the whole range, poverty gap effectiveness is highest in Hungary and lowest in Belgium, except for very large increases where it is lower in the UK.

[Figure 4.1 here]

4.4.2 Social Assistance

Figures 4.2a and 4.2b show equivalent results for changing social assistance benefit levels. There are some aspects that are in marked contrast to the effects of changing child benefits. First, the scale of the existing systems and hence the effects of proportional expansion/contraction on budgetary cost vary differently across countries. In contrast with its relatively large child benefit payments, Hungary has a very small social assistance scheme. The UK is the country with the costliest proportional expansion, because it starts with relatively high payments and high coverage. Second, the relationship between the poverty effects of benefit decreases and increases is different. Typically, increasing social assistance levels not only increases the income of current recipients but extends entitlement to those with higher income. Our methodology enables us to disentangle the part of poverty change which is related to changes in eligibility (that is, fewer/more benefit recipients) and the part related to changes in benefit levels for those already in receipt (Appendix Table 4.5). We find that indeed changes in the poverty headcount, as a result of scaling up/down the policy in Belgium, Bulgaria, Hungary and UK are driven by both changes in the benefit levels and coverage (although we should note that in Belgium, Bulgaria and Hungary we rarely see large total poverty changes). We draw the same conclusion for the changes in the poverty gap in all five countries considered, including Estonia (Appendix Table 4.6).

Depending on the composition of the relevant sections of the income distribution, the budgetary cost of increases could be higher than the budgetary savings from equivalent decreases. Figures 4.2a and 4.2b depict this in all five systems with the strongest cases being Estonia and Belgium. In Belgium and Bulgaria the effect on the poverty headcount of reducing social assistance is small, whereas the increase in poverty gap is relatively large, consistent with the finding of Tasseva (2016) for Bulgaria that most social assistance recipients are among those with incomes far below the poverty threshold. When scaling down social assistance, we again see decreasing rate of return of spending, that is, for larger decreases in social assistance benefit levels the reduction in total spending is smaller, due to small numbers of beneficiaries on very low incomes.

In contrast, in the UK reducing social assistance has a substantial effect on the poverty headcount (cutting it by 90% results in a 4pp increase), consistent with some existing recipients having incomes above the poverty threshold. Reductions add to the poverty rate and make budgetary savings even comparing the 70% with the 90% reduction scenario. This is because some social assistance entitlements take account of extra costs, such as for disability, and may bring recipient incomes a long way above the poverty threshold in the baseline. In Estonia the poverty headcount effect of expanding/contracting social assistance is very small and indeed there is no effect except for a 90% expansion (see Appendix Table 4.3). However, the effect on the poverty gap is dramatic, for a relatively small increase in GDP. This is consistent with the Estonian social assistance payments being very low relative to the poverty threshold. Even almost doubling them reduces the poverty gap by 1.5pp: more than in any of the other countries and at much lower cost (see the gradient in Figure 4.2b). Otherwise the poverty headcountcost gradients for benefit increases across countries are rather similar to each other but the poverty gap gradients vary more across countries with the effects being largest in Bulgaria (after Estonia) and smallest in Hungary. As with child benefits, in Belgium and the UK the poverty gap effectiveness of social assistance reduces with the size of the benefit, as larger shares of recipients are lifted above the poverty threshold.

[Figure 4.2 here]

4.4.3 Income tax threshold

The effects of increasing the income tax threshold on either poverty measure (see Figures 4.3a and 4.3b) are very small although the budgetary cost is large. For example, spending 1% of GDP in this way (and interpolating linearly where relevant) would reduce the poverty headcount by less than 1pp in all countries except Estonia (where the reduction is a little more). Most people paying income tax, benefiting from this policy change, are in households with income above the poverty threshold. However, the effects are not linear and the gradients are higher for smaller threshold increases, suggesting that there is scope for modest increases to reduce poverty (but at high cost relative to other strategies).

There is a similar picture for the poverty gap.

The situation is quite different when reducing the tax threshold. This has an effect on increasing poverty. The extra tax paid increases the numbers below the poverty threshold and the size of the poverty gap (Appendix Table 4.4), with the gradient being noticeably steeper in Estonia than in the other four countries. Reducing the tax-free income allowance by 90% would increase the poverty headcount by 7.4pp. This near-abolition scenario would increase the poverty rate in the remaining countries by between 2pp (Greece) and 3-4pp (Belgium, Italy and UK) (Appendix Table 4.3).

[Figure 4.3 here]

4.4.4 Re-scaling the whole tax-benefit system

To provide a benchmark for the individual policy instruments that we consider, Figure 4.4 shows the poverty cost-effectiveness of contracting/expanding the whole system by between -20% and +20%. It is notable that neither the budgetary cost of expansion nor the budgetary gain from contraction are the same size in GDP terms across countries, reflecting both differences in overall size of the systems and in the importance of monetary levels and thresholds in the systems. The cost effects are largest in Belgium and Italy (due at least in part to their large pension systems) and smallest in Estonia. The poverty cost-effectiveness also differs across countries with the largest poverty effects (in terms of both headcount and gap) per budgetary unit in Estonia and the UK and the smallest in Greece.

[Figure 4.4 here]

4.4.5 Comparisons across policy instruments

A comparison of the poverty effectiveness of the particular policy instruments is summarized in Table 4.2 by showing the poverty-cost ratios (gradients) evaluated for the -/+20% scenarios for the three instruments as well as the benchmark case of the whole tax-benefit system. For increases in the instruments, the higher the ratio the greater the poverty reduction for a given increase in spending (that is, cost-effectiveness). For reductions in the instruments, the higher the ratio the larger the poverty increase for a given budgetary gain.

Comparing within columns and between countries shows that increasing child benefits is most effective at reducing the headcount in Greece and Hungary and the gap in Italy and Hungary (numbers highlighted in bold). Reducing child benefits increases the headcount most for a given budgetary saving in the UK and the gap most in Hungary. Social assistance increases are most cost-effective for the headcount in Belgium and reductions cause the highest poverty increase for a given budgetary saving in Belgium as well as the UK. In Estonia changes in either direction have no effect on the headcount but are the most cost-effective at reducing the poverty gap. Changing income tax thresholds has the largest effects given costs in Estonia, for both the headcount and the gap. Increasing income tax thresholds is also cost-effective in reducing the poverty headcount and gap in Italy. Inflating the whole system is most cost-effective in Estonia and the UK (for the headcount) and Estonia and Bulgaria (for the gap). The reverse also applies: reducing all monetary levels has the most poverty-increasing effect given the budgetary gain in the same countries.

Comparing within countries (that is, across rows in Table 4.2) and focusing first on the poverty headcount, increasing social assistance is the most cost-effective option of the four considered in Belgium, the UK and Bulgaria (numbers underlined), and there are other policy instrument reductions that have a more damaging effect on poverty in all countries apart from Belgium. This is perhaps surprising, given its targeted nature. Child benefit increases are most cost-effective, compared to other policies, in reducing poverty in Greece and Italy, which do not have social assistance, and Hungary. In these three countries and in Bulgaria and especially the UK these are the most damaging to reduce for given budgetary saving, of the instruments considered. In Bulgaria and the UK this may be related to the partial income targeting of child benefits. In contrast, social assistance is the best performing instrument in poverty gap reduction effectiveness, as well as being the most damaging to reduce, in all countries with such an instrument with the exception of Hungary where social assistance is small. In Estonia the highest poverty headcount increase from a reduction in policy instrument arises with the income tax threshold and the most cost-effective change to reduce the poverty headcount is not any of the individual instruments but instead whole system expansion. This suggests that the policies that are mostly responsible for poverty reduction in this country are pensions and contributory (that is, maternity, parental and unemployment) benefits.

[Table 4.2 here]

4.5 Conclusions

Our analysis provides evidence on the relative effectiveness of different types of policy instrument in reducing the risk of poverty, or limiting its increase, by measuring the implications of increasing or reducing the scale of the instrument within its national context.

The assessment of the most cost-effective instrument depends on whether the poverty headcount or poverty gap is used as the outcome indicator and on the direction and scale of the change in some instruments and countries and not others. Nevertheless, our results show that the most preferred options in terms of poverty reduction cost-effectiveness are child benefits and social assistance. Based on the poverty headcount increasing social assistance is the most cost-effective approach of those considered in Belgium, Bulgaria and the UK. Child benefit increases are the most effective option considered in Greece, Hungary and Italy. In Estonia the benchmark case of re-scaling all monetary components is actually more cost-effective than any of the single options.

It is important to look at the poverty gap as well as the poverty headcount in evaluating cost-effectiveness. The effect of social assistance in Estonia provides a good illustration. As the 2013 level of social assistance is very low relative to the poverty threshold, its increase makes no difference to the headcount unless it is scaled up to be almost double its current value but scores very highly in terms of cost-effectiveness when the effect on the poverty gap is measured.

The effects are not always linear nor are they always symmetrical for increases and decreases in the instruments. For example, increasing income tax thresholds has little effect on poverty but lowering them would have a larger negative effect. Nevertheless, except in Estonia, this negative effect is smaller for a given budgetary gain than would occur if any of the other instruments were reduced in size. This suggests that a revenue-neutral combination of reduction to the tax threshold and increase in child benefit could be a promising path for policy makers interested in cost-effective poverty reduction. On the other hand, reducing child benefits is a particularly damaging way to make budgetary cuts, given the implications for the increase in the poverty headcount. This applies in countries with both high and low average child benefit payments and high and low benefit prevalence.

More generally, our approach to measuring the poverty reducing effectiveness of single policy instruments can inform the design of policy packages, combining changes to more than one instrument. For example, similar analysis of the implications for poverty of increasing the minimum wage level (Leventi et al., 2017) shows that this is not well targeted on people in households with income below the poverty threshold and is therefore a policy approach that will not achieve poverty reduction on its own. Nevertheless, minimum wages reduce the need for in-work benefits and help to make work pay (Immervoll and Pearson, 2009) and are therefore suitable for combining with increases in social assistance into a package that reduces poverty while minimizing damage to incentives to work (Collado et al., 2016).

The limitations of our approach relate to the choice of policy instruments that are compared. First, in countries without one of the policy instruments as part of its system, the relative effectiveness of the remaining instruments is enhanced. For example, if Greece had a minimum income social assistance scheme in place then its child benefits might look less effective than they do in its absence. Second, the instruments analysed were chosen partly because they exist in many of the seven countries. There are other less common instruments that are relevant in particular national contexts, such as in-work benefits, targeted tax credits and housing benefits. As the Estonian case suggests, the most cost-effective poverty-reducing instrument may not be one of those analysed here. In a single country context, it would be possible to test all relevant policy instruments using our approach. Comparing across countries, we have demonstrated how, using microsimulation techniques, we can take account of the national diversity in existing policy systems, population characteristics and economic circumstances at a common point in time to assess the relative poverty-reducing cost-effectiveness of policies with similar goals.

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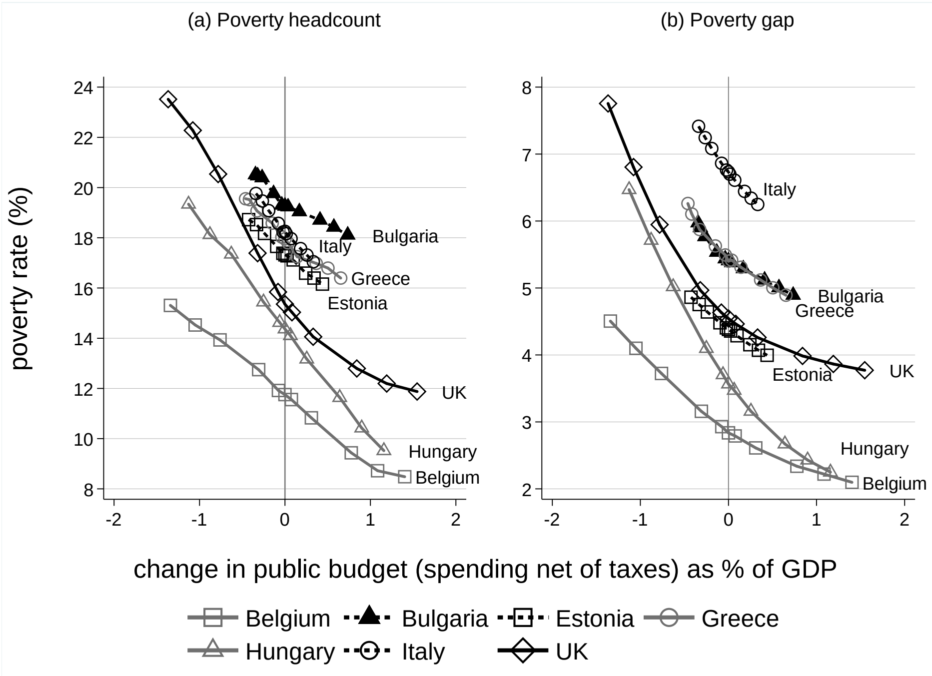
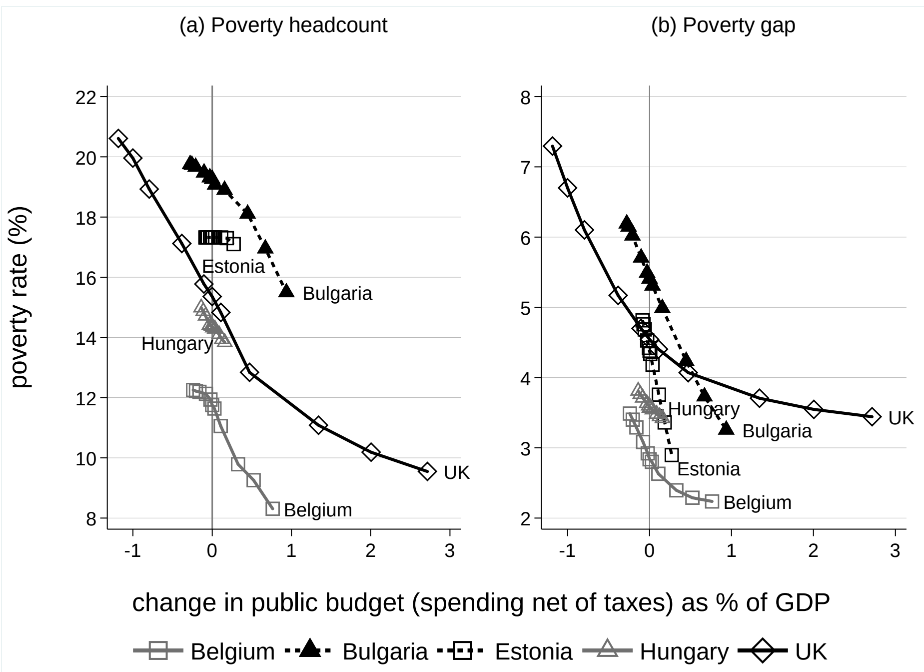
4.6 Figures

Figure 4.1: *Child benefit levels: poverty vs. cost*



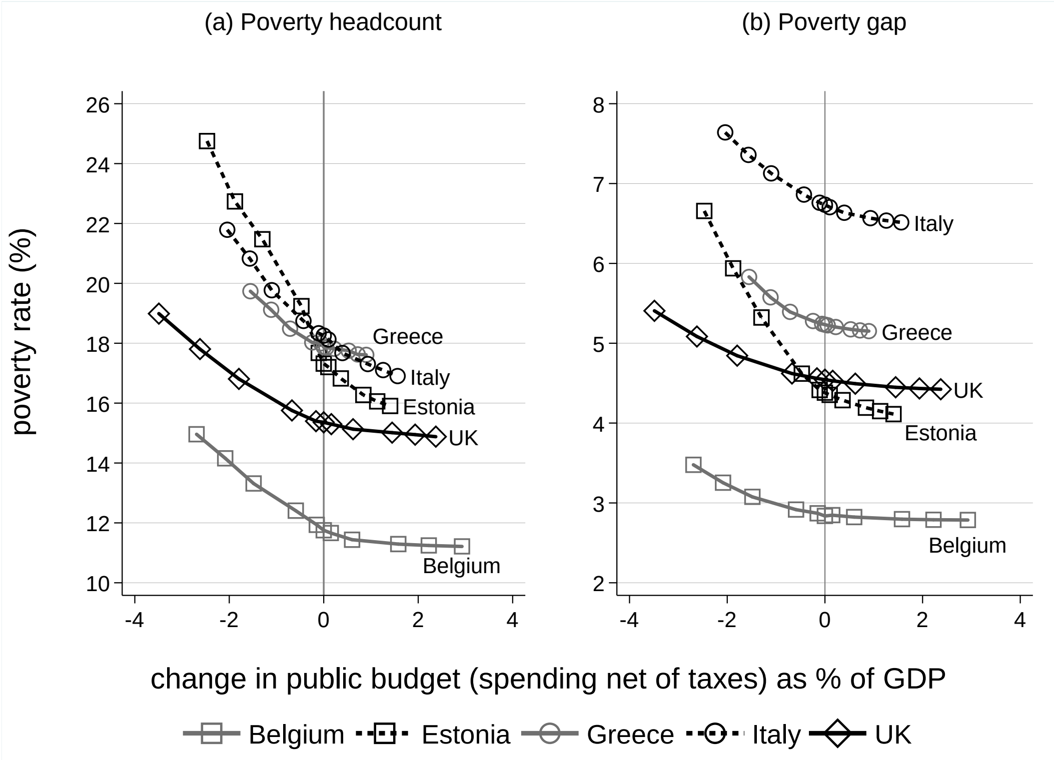
Source: Authors calculations using EUROMOD and EU-SILC. *Notes:* Reading from left to right, the instruments are decreased by 90%, 70%, 50%, 20% and 5% and increased by 5%, 20%, 50%, 70% and 90%. Poverty is measured using a fixed threshold, 60% of median equivalised household disposable income under the 2013 baseline policy system. The poverty gap is expressed as a ratio of the poverty line. The change in the public budget is the direct effect of changing the instruments net of any interactions with the rest of the tax-benefit system, as a percentage of 2013 GDP.

Figure 4.2: *Social assistance minimum income levels: poverty vs. cost*



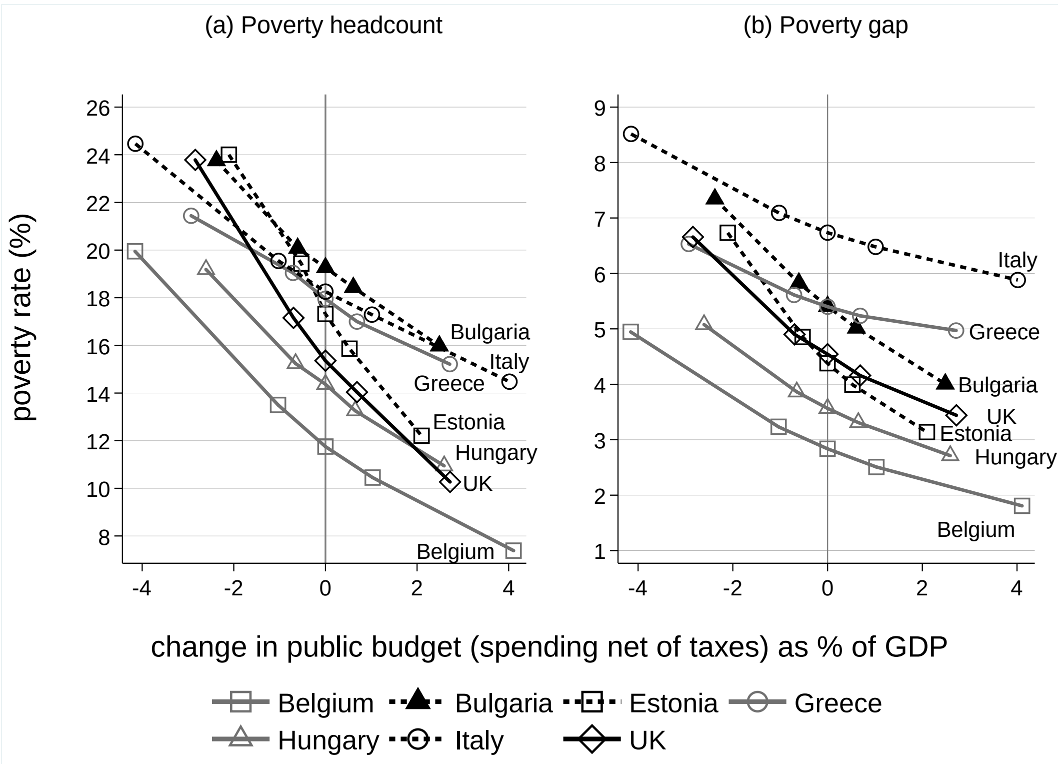
Source and notes: see Figure 4.1. There is no national social assistance benefit in Greece and Italy.

Figure 4.3: *Income tax thresholds: poverty vs. cost*



Source and notes: see Figure 4.1. There is no income tax zero rate band in Bulgaria and Hungary.

Figure 4.4: *Rescaling the whole system: poverty vs. cost*



Source and notes: see Figure 4.1. Here the system is decreased and increased by 5% and 20%.

4.7 Tables

Table 4.1:
Policy instruments: existing gross levels as a percentage of median equivalent household disposable income, 2013

		Belgium	**Bulgaria**	**Estonia**	**Greece**	**Italy**	**Hungary**	**UK**
Child benefits	Mean for recipients %	19.2	10.7	7.9	6.0	8.6	27.5	24.5
	% households receiving	25.5	7.6	18.5	18.4	12.9	19.2	20.8
Social Assistance Benefits	Mean for recipients %	26.6	12.1	17.1	-	-	21.6	23.2
	% households receiving	1.9	7.1	2.6	-	-	0.3	14.0
Income tax threshold	Threshold level %	34.1	-	26.2	52.2	52.0	-	64.3
Median equivalised household disposable income EUR/month		*1,707*	*293*	*550*	*799*	*1,282*	*360*	*1,450*

Source: Authors' calculations using EUROMOD with EU-SILC
Notes: Household disposable income is equivalised using the modified OECD scale in order to take differences in household composition into account. The scale attributes a weight of 1 to the head of the household, a weight of 0.5 to every person above the age of 14 and a weight of 0.3 to every child aged 014. Euro exchange rates: BG 1.956BGN; HU 286.0HUF; UK 0.8553GBP.

Table 4.2:
Poverty-cost ratio by policy instrument

	Child benefit		**Social Assistance**		**Income tax threshold**		**Whole tax-benefit system**	
	Poverty headcount							
	-20%	*20%*	*-20%*	*20%*	*-20%*	*20%*	*-20%*	*20%*
Belgium	3.23	2.99	**4.68**	**6.48**	1.11	0.53	1.97	1.06
Bulgaria	3.76	1.31	2.04	2.32			1.89	1.32
Estonia	3.49	2.09	0.00	0.00	**4.05**	**1.37**	**3.17**	**2.44**
Greece	4.20	**4.99**			0.64	0.25	1.19	1.32
Hungary	**4.28**	**4.70**	1.33	2.51			1.85	1.32
Italy	4.08	4.08			1.14	**1.47**	1.50	0.94
UK	**6.34**	3.93	**4.61**	5.34	0.59	0.37	**2.97**	**1.87**
	Poverty gap							
	-20%	*20%*	*-20%*	*20%*	*-20%*	*20%*	*-20%*	*20%*
Belgium	0.98	0.80	2.83	2.11	0.10	0.06	0.51	0.25
Bulgaria	0.97	0.70	2.91	2.68			**0.82**	**0.56**
Estonia	1.03	0.97	**5.27**	**5.35**	**0.50**	**0.26**	**1.11**	**0.59**
Greece	1.16	1.02			0.19	0.13	0.39	0.16
Hungary	**2.03**	**1.68**	1.36	1.29			0.58	0.33
Italy	1.32	**2.11**			0.24	**0.32**	0.42	0.22
UK	**1.32**	0.86	1.63	1.01	0.11	0.08	0.76	0.39

Source: Authors' calculations using EUROMOD and EU-SILC.
Notes: The poverty-cost indicator is calculated as the ratio of the change in poverty headcount or gap (using a fixed poverty threshold) to the change in public budget measured as a % of GDP, using the -20% and the +20% change in policy for child benefit, social assistance, income tax and whole system re-scaling (the gradient of the curves in Figures 1, 2, 3 and 4). The countries with the highest poverty-cost ratio for each scenario for a particular policy instrument (i.e. within columns) are indicated in **bold** (two countries for the policy instruments applying in all seven cases, one country for the other instruments). The most cost-effective policy instrument within countries for each scenario is shown underlined.

4.8 Appendix

Table 4.3:
Change in poverty headcount ratio between baseline and policy scenarios (in % points)

Country	Baseline rate (%)	Decrease by ...					Increase by ...				
		90%	70%	50%	20%	5%	5%	20%	50%	70%	90%
Child benefits											
Belgium	11.8	3.6 ***	2.8 ***	2.2 ***	1.0 ***	0.2 **	-0.2 ***	-0.9 ***	-2.3 ***	-3.0 ***	-3.3 ***
Bulgaria	19.3	1.3 ***	1.2 ***	1.1 ***	0.5 ***	0.0	0.0	-0.2 ***	-0.6 ***	-0.8 ***	-1.2 ***
Estonia	17.3	1.4 ***	1.2 ***	0.9 ***	0.3 ***	0.1	0.0	-0.2 ***	-0.7 ***	-0.9 ***	-1.2 ***
Greece	18.0	1.6 ***	1.6 ***	1.1 ***	0.6 ***	0.1 **	-0.2 **	-0.7 ***	-1.0 ***	-1.2 ***	-1.6 ***
Hungary	14.4	5.0 ***	3.8 ***	3.0 ***	1.1 ***	0.3 ***	-0.3 ***	-1.2 ***	-2.7 ***	-3.9 ***	-4.8 ***
Italy	18.3	1.5 ***	1.2 ***	0.8 ***	0.3 ***	0.0	-0.1 ***	-0.3 ***	-0.7 ***	-0.9 ***	-1.2 ***
UK	15.4	8.2 ***	6.9 ***	5.2 ***	2.0 ***	0.5 ***	-0.3 ***	-1.3 ***	-2.6 ***	-3.2 ***	-3.5 ***
Social assistance											
Belgium	11.8	0.5 ***	0.5 ***	0.4 ***	0.4 ***	0.2 ***	-0.1 **	-0.7 ***	-2.0 ***	-2.5 ***	-3.4 ***
Bulgaria	19.3	0.5 ***	0.5 ***	0.4 ***	0.2 **	0.1	-0.2 *	-0.4 ***	-1.2 ***	-2.3 ***	-3.8 ***
Estonia	17.3	0.0 ***	0.0 ***	0.0 ***	0.0 ***	0.0 ***	0.0 ***	0.0 ***	0.0 ***	0.0	-0.2 **
Greece	18.0										
Hungary	14.4	0.6 ***	0.5 ***	0.3 ***	0.0 **	0.0	0.0	-0.1 **	-0.3 ***	-0.4 ***	-0.5 ***
Italy	18.3										
UK	15.4	5.3 ***	4.6 ***	3.6 ***	1.8 ***	0.4 ***	-0.5 ***	-2.5 ***	-4.3 ***	-5.2 ***	-5.8 ***
Income tax threshold											
Belgium	11.8	3.2 ***	2.4 ***	1.6 ***	0.7 ***	0.2 ***	-0.1 **	-0.3 ***	-0.5 ***	-0.5 ***	-0.5 ***
Bulgaria	19.3										
Estonia	17.3	7.4 ***	5.4 ***	4.2 ***	1.9 ***	0.4 ***	-0.1 **	-0.5 ***	-1.0 ***	-1.3 ***	-1.4 ***
Greece	18.0	1.9 ***	1.2 ***	0.6 ***	0.2	0.1	0.0	-0.1 **	-0.1 ***	-0.2 ***	-0.3 ***
Hungary	14.4										
Italy	18.3	3.5 ***	2.6 ***	1.5 ***	0.5 ***	0.1 ***	-0.1 ***	-0.6 ***	-1.0 ***	-1.2 ***	-1.4 ***
UK	15.4	3.6 ***	2.4 ***	1.5 ***	0.4 ***	0.0 ***	-0.1 ***	-0.2 ***	-0.3 ***	-0.4 ***	-0.5 ***
Whole tax-benefit system											
Belgium	11.8	47.1 ***	36.0 ***	25.8 ***	8.2 ***	1.7 ***	-1.3 ***	-4.4 ***	-8.0 ***	-8.8 ***	-9.4 ***
Bulgaria	19.3	16.2 ***	15.1 ***	11.6 ***	4.5 ***	0.8 ***	-0.8 ***	-3.3 ***	-7.5 ***	-10.3 ***	-12.0 ***
Estonia	17.3	23.8 ***	19.7 ***	15.6 ***	6.7 ***	2.1 ***	-1.5 ***	-5.1 ***	-8.0 ***	-9.2 ***	-10.6 ***
Greece	18.0	33.3 ***	23.6 ***	15.5 ***	3.5 ***	1.1 ***	-1.0 ***	-2.7 ***	-3.7 ***	-4.0 ***	-4.6 ***
Hungary	14.4	38.0 ***	31.4 ***	20.6 ***	4.8 ***	0.9 ***	-1.1 ***	-3.4 ***	-6.7 ***	-8.0 ***	-8.6 ***
Italy	18.3	37.0 ***	30.3 ***	20.7 ***	6.2 ***	1.3 ***	-1.0 ***	-3.8 ***	-6.1 ***	-7.0 ***	-7.5 ***
UK	15.4	35.2 ***	27.1 ***	20.9 ***	8.4 ***	1.8 ***	-1.3 ***	-5.1 ***	-8.0 ***	-9.1 ***	-9.7 ***

Source: Authors' calculations using EUROMOD and EU-SILC.
Notes: The baseline poverty rate is based on 2013 incomes and policies. The poverty threshold is 60% of the 2013 baseline median equivalised household disposable income. The baseline value for Greece is slightly different in the income tax threshold scenario because the 2012 tax threshold has been re-introduced. Shaded cells indicate that in 2013 there was no national social assistance benefit in Greece and Italy and no income tax zero rate band in Bulgaria and Hungary. Significance levels indicated as $*\ p < 0.1$, $**\ p < 0.05$, $***\ p < 0.01$.

Table 4.4:
Change in poverty gap ratio between baseline and policy scenarios (in % points)

Country	Baseline gap	Decrease by …					Increase by …				
		90%	70%	50%	20%	5%	5%	20%	50%	70%	90%
							Child benefits				
Belgium	2.8	1.6 ***	1.2 ***	0.9 ***	0.3 ***	0.1 ***	-0.1 ***	-0.2 ***	-0.5 ***	-0.6 ***	-0.8 ***
Bulgaria	5.4	0.6 ***	0.5 ***	0.4 ***	0.1 ***	0.0 ***	0.0 ***	-0.1 ***	-0.3 ***	-0.4 ***	-0.5 ***
Estonia	4.4	0.5 ***	0.4 ***	0.3 ***	0.1 ***	0.0 ***	0.0 ***	-0.1 ***	-0.2 ***	-0.3 ***	-0.4 ***
Greece	5.4	0.8 ***	0.6 ***	0.4 ***	0.2 ***	0.0 ***	0.0 ***	-0.1 ***	-0.3 ***	-0.5 ***	-0.6 ***
Hungary	3.6	2.9 ***	2.1 ***	1.4 ***	0.5 ***	0.1 ***	-0.1 ***	-0.4 ***	-0.9 ***	-1.2 ***	-1.3 ***
Italy	6.7	0.7 ***	0.5 ***	0.3 ***	0.1 ***	0.0	-0.1 ***	-0.1 ***	-0.3 ***	-0.4 ***	-0.5 ***
UK	4.5	3.2 ***	2.3 ***	1.4 ***	0.4 ***	0.1 ***	-0.1 ***	-0.3 ***	-0.6 ***	-0.7 ***	-0.8 ***
							Social assistance				
Belgium	2.8	0.6 ***	0.5 ***	0.4 ***	0.2 ***	0.1 ***	-0.1 ***	-0.2 ***	-0.5 ***	-0.6 ***	-0.6 ***
Bulgaria	5.4	0.8 ***	0.7 ***	0.6 ***	0.3 ***	0.1 ***	-0.1 ***	-0.4 ***	-1.2 ***	-1.7 ***	-2.1 ***
Estonia	4.4	0.4 ***	0.4 ***	0.3 ***	0.1 ***	0.0 ***	0.0 ***	-0.2 ***	-0.6 ***	-1.0 ***	-1.5 ***
Greece	5.4										
Hungary	3.6	0.2 ***	0.2 ***	0.1 ***	0.0 ***	0.0 ***	0.0 ***	0.0 ***	-0.1 ***	-0.1 ***	-0.2 ***
Italy	6.7										
UK	4.5	2.8 ***	2.2 ***	1.6 ***	0.6 ***	0.2 ***	-0.1 ***	-0.5 ***	-0.8 ***	-1.0 ***	-1.1 ***
							Income tax threshold				
Belgium	2.8	0.6 ***	0.4 ***	0.2 ***	0.1 ***	0.0 ***	0.0 ***	0.0 ***	-0.1 ***	-0.1 ***	-0.1 ***
Bulgaria	5.4										
Estonia	4.4	2.3 ***	1.6 ***	0.9 ***	0.2 ***	0.0 ***	0.0 ***	-0.1 ***	-0.2 ***	-0.2 ***	-0.3 ***
Greece	5.2	0.6 ***	0.3 ***	0.2 ***	0.0 ***	0.0 ***	0.0 ***	0.0 ***	-0.1 ***	-0.1 ***	-0.1 ***
Hungary	3.6										
Italy	6.7	0.9 ***	0.6 ***	0.4 ***	0.1 ***	0.0	-0.1 ***	-0.1 ***	-0.2 ***	-0.2 ***	-0.2 ***
UK	4.5	0.9 ***	0.5 ***	0.3 ***	0.1 ***	0.0 ***	0.0 ***	-0.1 ***	-0.1 ***	-0.1 ***	-0.1 ***
							Whole tax-benefit system				
Belgium	2.8	29.3 ***	18.2 ***	9.7 ***	2.1 ***	0.4 ***	-0.3 ***	-1.0 ***	-1.7 ***	-1.8 ***	-1.9 ***
Bulgaria	5.4	14.4 ***	10.5 ***	6.5 ***	1.9 ***	0.4 ***	-0.4 ***	-1.4 ***	-2.9 ***	-3.5 ***	-3.9 ***
Estonia	4.4	19.6 ***	13.5 ***	8.4 ***	2.3 ***	0.5 ***	-0.4 ***	-1.2 ***	-2.3 ***	-2.8 ***	-3.2 ***
Greece	5.4	20.5 ***	11.7 ***	5.6 ***	1.1 ***	0.2 ***	-0.2 ***	-0.4 ***	-0.6 ***	-0.5 ***	-0.4 **
Hungary	3.6	25.4 ***	14.9 ***	7.0 ***	1.5 ***	0.3 ***	-0.3 ***	-0.9 ***	-1.5 ***	-1.7 ***	-1.7 ***
Italy	6.8	24.7 ***	15.1 ***	7.7 ***	1.8 ***	0.3 ***	-0.3 ***	-0.9 ***	-1.5 ***	-1.8 ***	-2.0 ***
UK	4.5	22.9 ***	14.4 ***	8.5 ***	2.2 ***	0.4 ***	-0.3 ***	-1.1 ***	-1.7 ***	-2.0 ***	-2.1 ***

Source and notes: The poverty gap is expressed as a ratio of the poverty line. For further details, see Table 4.3.

Table 4.5:

Decomposing the total change in poverty headcount ratio between baseline and social assistance policy scenario (in % points) into changes in coverage (cov.) and level

Country	Base-line rate (%)	Decrease by ...														
		90%			70%			50%			20%			5%		
		Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level
Belgium	11.8	0.5	0.3	0.2	0.5	0.2	0.2	0.4	0.2	0.3	0.4	0.1	0.3	0.2	0.0	0.2
Bulgaria	19.3	0.5	0.3	0.1	0.5	0.1	0.4	0.4	0.1	0.4	0.2	0.0	0.2	0.1	0.0	0.1
Estonia	17.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Greece	18.0															
Hungary	14.4	0.6	0.2	0.5	0.5	0.1	0.4	0.3	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0
Italy	18.3															
UK	15.4	5.3	1.3	4.0	4.6	1.1	3.5	3.6	0.8	2.8	1.8	0.2	1.5	0.4	0.0	0.4
		Increase by ...														
		5%			20%			50%			70%			90%		
		Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level
Belgium	11.8	-0.1	0.0	-0.1	-0.7	-0.2	-0.5	-2.0	-0.7	-1.3	-2.5	-1.0	-1.5	-3.4	-1.7	-1.7
Bulgaria	19.3	-0.2	-0.1	-0.1	-0.4	-0.2	-0.2	-1.2	-0.4	-0.8	-2.3	-1.1	-1.2	-3.8	-2.2	-1.6
Estonia	17.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.2	-0.2	0.0
Greece	18.0															
Hungary	14.4	0.0	0.0	0.0	-0.1	0.0	-0.1	-0.3	0.0	-0.3	-0.4	0.0	-0.4	-0.5	0.0	-0.5
Italy	18.3															
UK	15.4	-0.5	-0.1	-0.5	-2.5	-0.3	-2.2	-4.3	-0.6	-3.7	-5.2	-0.7	-4.5	-5.8	-0.9	-5.0

Source and notes: The sum of the poverty change due to changes in the tax/benefit i) coverage and ii) level adds up to 100% of the total change in the poverty headcount. The change in the poverty headcount due to changes in the tax/benefit levels captures the in/out-of-poverty transitions of only those households who experienced a change in the tax/benefit level, conditional on non-zero taxes/benefits in the baseline. The change in the poverty headcount due to changes in the tax/benefit coverage captures the in/out-of-poverty transitions of only those households who had non-zero taxes/benefits in the baseline but zero in the reform scenario and vice versa. In the different scenarios, we focus on changes in the level/coverage of (all) child benefits, social assistance benefits and income taxes. For further details, see Table 4.3.

Table 4.6:
Decomposing the total change in poverty gap ratio between the baseline and social assistance policy scenario (in % points) into changes in coverage (cov.) and level

Country	Base -line gap	Decrease by ...														
		90%			70%			50%			20%			5%		
		Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level
Belgium	2.8	0.6	0.3	0.3	0.5	0.2	0.3	0.4	0.1	0.3	0.2	0.1	0.2	0.1	0.0	0.1
Bulgaria	5.4	0.8	0.7	0.1	0.7	0.3	0.5	0.6	0.2	0.5	0.3	0.1	0.2	0.1	0.0	0.1
Estonia	4.4	0.4	0.2	0.2	0.4	0.1	0.2	0.3	0.1	0.2	0.1	0.0	0.1	0.0	0.0	0.0
Greece	5.4															
Hungary	3.6	0.2	0.0	0.2	0.2	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Italy	6.7															
UK	4.5	2.8	0.7	2.1	2.2	0.6	1.6	1.6	0.4	1.2	0.6	0.1	0.5	0.2	0.0	0.1
		Increase by ...														
		5%			20%			50%			70%			90%		
		Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level	Total	Cov.	Level
Belgium	2.8	-0.1	0.0	-0.1	-0.2	-0.1	-0.2	-0.5	-0.2	-0.3	-0.6	-0.2	-0.3	-0.6	-0.3	-0.4
Bulgaria	5.4	-0.1	0.0	-0.1	-0.4	-0.2	-0.3	-1.2	-0.5	-0.7	-1.7	-0.7	-1.0	-2.1	-0.8	-1.3
Estonia	4.4	0.0	0.0	0.0	-0.2	0.0	-0.2	-0.6	-0.2	-0.4	-1.0	-0.4	-0.6	-1.5	-0.7	-0.8
Greece	5.4															
Hungary	3.6	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	-0.1	-0.1	0.0	-0.1	-0.2	0.0	-0.2
Italy	6.7															
UK	4.5	-0.1	0.0	-0.1	-0.5	-0.1	-0.4	-0.8	-0.1	-0.7	-1.0	-0.2	-0.8	-1.1	-0.2	-0.9

Source and notes: The poverty gap is expressed as a ratio of the poverty line. The change in the poverty gap due to changes in the benefit levels captures the poverty gap changes of households who experienced a change in the social assistance (SA) benefit level, conditional on non-zero SA benefits in the baseline. The change in the poverty gap due to changes in the SA benefit coverage captures the poverty gap changes of households who had non-zero SA benefits in the baseline but zero in the reform scenario and vice versa. For further details, see Table 4.5.