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The Changing Education Distribution and Income Inequality in Great Britain*

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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.

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Keywords: higher education expansion; income distribution; decomposition

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1 Introduction

Over the past years, there has been an unprecedented increase in the number of individuals in Higher Education in Great Britain. The share of individuals completing full-time education aged 16 fell by 25% between 2001 and 2011; whilst the share of individuals completing education aged 17-19 increased by 37% and the share of those completing education aged 20+ (in Higher Education) increased for females by 34% and for males by 31% (Table 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).

"place Table 1 here"

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.[1] 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.[2] 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 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

[1] 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.

[2] 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.

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 that the education earnings differentials have remained broadly unchanged 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, overall we find no evidence for a 'compression' effect in the full period 2001-11.

Second, we find evidence for an 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 3.6% due to HE expansion and it rose a further 3% 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 and 2007 and 2011, we find that overall income inequality for the middle 95% of the income distribution remained broadly unchanged. This was despite the upward pressure due to education and is due to changes in the tax-benefit system. We show that tax-benefit policies been equalising (consistent with e.g. Sefton et al. (2009), Hills et al. (2016b), Paulus et al. (2019)), by benefiting mostly the bottom of the income 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.

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.[3]

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.

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

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

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

$$\Delta I = f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_0, r_0, p_0, e_0, x_0, y_0, o_0) \tag{1}$$

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 the identity:

$$\begin{aligned} \Delta I = & \underbrace{f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_1, r_1, p_1, e_0, x_0, y_0, o_0)}_{\text{population characteristics and market income effect (nominal)}} + \\ & \underbrace{f(d_1, r_1, p_1, e_0, x_0, y_0, o_0) - f(d_0, r_0, p_0, e_0, x_0, y_0, o_0)}_{\text{tax-benefit policy effect (nominal)}} \end{aligned} \tag{2}$$

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 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:

$$\begin{aligned} \Delta I = & \underbrace{f(d_1, r_1, p_1, e_1, x_1, y_1, o_1) - f(d_1, r_1, p_1, e_0, x_0, \alpha y_0, \alpha o_0)}_{\text{i) population characteristics and market income effect (real)}} + \\ & \underbrace{f(d_1, r_1, p_1, e_0, x_0, \alpha y_0, \alpha o_0) - f(d_0, r_0, \alpha p_0, e_0, x_0, \alpha y_0, \alpha o_0)}_{\text{ii) tax-benefit policy effect (real)}} + \\ & \underbrace{f(d_0, r_0, \alpha p_0, e_0, x_0, \alpha y_0, \alpha o_0) - f(d_0, r_0, p_0, e_0, x_0, y_0, o_0)}_{\text{iii) nominal effect}} \end{aligned} \tag{3}$$

For a scale-dependent measure (e.g. mean income), the sum of the first two terms in equation 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)).

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 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{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:

$$
\begin{aligned}
\ln y^{wBm}_{i(ht)} &= x^{wBm}_{i(ht)}\beta_t + e^{wBm}_{i(ht)}\lambda_t + \epsilon_{i(ht)} \\
\ln y^{nwBm}_{i(ht)} &= x^{nwBm}_{i(ht)}\gamma_t + e^{nwBm}_{i(ht)}\delta_t + \eta_{i(ht)} \\
\ln y^{wBf}_{i(ht)} &= x^{wBf}_{i(ht)}\pi_t + e^{wBf}_{i(ht)}\nu_t + \mu_{i(ht)} \\
\ln y^{nwBf}_{i(ht)} &= x^{nwBf}_{i(ht)}\rho_t + e^{nwBf}_{i(ht)}\theta_t + \upsilon_{i(ht)}
\end{aligned}
\tag{5}
$$

where $\ln y^{wBm}_{i(ht)}$, $\ln y^{nwBm}_{i(ht)}$, $\ln y^{wBf}_{i(ht)}$ and $\ln y^{nwBf}_{i(ht)}$ 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 $\upsilon_{i(ht)}$.[4] 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 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), which minimises a function of the differences between the base and target weights. In more detail, the household survey data weights in $t = 1$ (*base weights*) are adjusted, so that the education shares (completed education aged

[4]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 5.

16 or less, aged 17-19, aged 20+) in $t = 1$ correspond to the education shares in $t = 0$ (*target weights*). Furthermore, we account for the relative change in education shares along the following dimensions: age (5-year bands), sex (male/female) and household type (with/without children and with 1/2+ adults in the household).[5] 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 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.

Finally, we provide bootstrapped standard errors for the change in mean income and income inequality. We construct a bootstrap sample for each data year by sampling households with replacement and drawing the same number of households as the unweighted sample. We draw 400 bootstrap samples and carry out the decomposition analysis for each one of them. Our estimates account for sample variation

[5]We make use of the Stata command reweight2 by Browne (2012).

but not measurement error.

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 (DWP, 2005; DWP, 2014a; DWP, 2014b). 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 (2019) and the Institute for Fiscal Studies (see Bourquin et al. (2019)).[6]

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 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 (version G2.12) 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

[6]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.

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.

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.

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 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 standard deviation of income to the mean).

Inequality remained broadly unchanged between 2001 and 2007 and between 2007 and 2011. In the crisis years 2007-11, there was a statistically significant drop in inequality only for the Atkinson index with aversion parameter of 2. In 2011, the Gini coefficient was 0.27; the Atkinson index with aversion parameter of 0.5, 1 and 2 was 0.06, 0.11 and 0.19, respectively; the coefficient of variation was 0.53.

"place Table 2 here"

To understand better what is behind the inequality changes, Figure 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. Incomes increased for the first 6 ventile groups, with the strongest growth of more than 5% enjoyed by households from the first to fourth income ventiles. The richest 20th ventile also experienced a small income gain of 1.6%, although this was not statistically significantly different from 0. For the rest of the distribution incomes fell by 0.3% (10th ventile) to 1.5% (19th ventile), although again these changes were not statistically significant.

"place Figure 1 here"

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.

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 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 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.

We find a small drop of 0.28 in average household net income, statistically significant at the 10% level, due to reduction in the HE wage premium among white British female workers. But we do not find any changes to the HE wage premium among male workers or non-white-British female workers and hence, they do not have any impact on the income distribution. 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.

"place Figure 2 here"

Figure 3 shows results for breaking down 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 they may also partly offset the inequality-reducing impact of more equally distributed market incomes.

The most striking feature of Figure 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 6% but 2.1 percentage points was lost to lower benefit entitlements and/or higher tax/NI liabilities. The loss of earnings between the first and sixth ventiles due to wage changes was small and only statistically significant (at the 10% significance level) for the second ventile. In contrast, earnings rose for the rest of the distribution due to wage changes. 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 (4%), self-employment income (0.5%) and other types of market incomes such as private pensions (0.8%) and investment income (0.4%). 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 somewhat more equally distributed across households. Tax-benefit policies partly offset the income gains due to HE expansion.

A final notable feature of Figure 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) and Blundell et al. (2018) 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. Belfield et al. (2017) 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.

"place Figure 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 1.6%, although this was not statistically significantly different from zero (Figure 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 income losses along the entire distribution apart from the 17th to 20th ventiles where incomes changes were not statistically significant. Mean net income rose by 3% due to the expansion in education: There were income gains at all parts of the distribution – somewhat larger for the first and last ventiles – which were overall more equally distributed across decile groups, compared to the 2001-07 period.

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.

"place Figure 4 here"

Breaking down the PCMI components in 2007-11 by income source (Figure 5) shows that earnings fell in the 10th, 13th and 15th ventiles (for the rest of the distribution changes were not statistically significant) due to wage changes but the losses were partly offset by the automatic stabilisation effect of policies.

HE expansion contributed to statistically significant increases in mean earnings (2.5%) and other market incomes, in particular private pensions (1%). Increases in investment income were smaller, at 0.2%. The tax-benefit system, through automatic stabilisation, partly reduced the income gains due to changes in the education composition.

The residual captures losses in market incomes throughout most of the distribution which can be largely attributed to the increase in unemployment during the crisis; while earnings growth in the first to fourth 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 5%.

“place Figure 5 here”

Figure 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 with 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 Paulus et al. (2019) 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.

“place Figure 6 here”

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 3 and Table 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). As in the previous section, we further decompose the PCMI effects into its subcomponents. We find that changes to the education composition was the main factor contributing to higher inequality in 2001-07. Although education composition changes continued to raise inequality in 2007-11, their contribution was smaller than in 2001-07 and no longer statistically significant.

In more detail, we find that wage changes did not have any statistically significant effect on inequality. Looking at the wage returns to HE in the growth period, only changes to the returns for white British female workers were slightly equalising for the Gini and Atkinson index with aversion parameter of 2. There was no effect on the other inequality measures. The returns to HE among male and non-white-British female workers remained broadly unchanged and hence, did not affect income inequality. In the crisis years, the continued absence of changes to the HE wage premia also led to no effect on inequality. Hence, overall we find no evidence for the 'compression' effect of HE expansion on inequality in the 2000s.

Moving to changes to the education composition, we find that the increase in HE attainment led to higher income inequality in the 2000s and this was mainly driven by changes in the pre-crisis period. Our results show that, in the 2001-07 period, HE expansion is the main component of the PCMI effect that explains the rise in net income inequality. In 2007-11, the gains from HE expansion were more equally distributed than in 2001-07. Thus, education changes continued to widen the gap between rich and poor but to a smaller extent and the effect was no longer statistically significant.

The residual did not have any statistically significant impact on inequality in either period, although between 2007 and 2011 its size was relatively big.

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 less evidence for a reduction in inequality at higher levels of education attainment (Blanden and Macmillan, 2014; Crawford, 2012).

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. Paulus et al. 2019, De Agostini et al. 2016).

"place Table 3 here"

"place Table 4 here"

5 Conclusions

The share of individuals with HE (those who completed full-time education aged 20+) in Great Britain increased by 33% 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 as 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 little 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.

However, between 2007 and 2011 we find that the income gains due to education composition changes were more equally distributed than in 2001-07. This suggests that further HE expansion may start lowering inequality as fewer low-educated people remain. Furthermore, 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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Tables

Table 1: *Education shares by age at which completed full-time education (in %)*

	2001	2007	2011
Males			
aged 16 or less	60.1	53.3	45.7
aged 17-19	19.1	21.7	26.9
aged 20+	20.9	25.0	27.4
Females			
aged 16 or less	57.1	50.1	42.5
aged 17-19	23.4	25.8	31.3
aged 20+	19.5	24.1	26.1
All			
aged 16 or less	58.6	51.7	44.1
aged 17-19	21.3	23.8	29.1
aged 20+	20.2	24.5	26.8

Notes: Sample includes individuals aged 15 to 64. Individuals are classified into the three categories using information on age completed full-time education (Family Resources Survey variable 'tea') or, if missing, using information on their age and whether presently in full-time education (variable 'fted').

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

Table 2: *Level of and changes (in % points) to inequality*

	Gini	Atkinson (0.5)	Atkinson (1)	Atkinson (2)	CV
observed 2001	.277***	.060***	.114***	.206***	.532***
	(.002)	(.001)	(.001)	(.002)	(.005)
observed 2007	.275***	.059***	.112***	.202***	.530***
	(.002)	(.001)	(.002)	(.002)	(.006)
observed 2011	.268***	.056***	.106***	.190***	.526***
	(.003)	(.001)	(.002)	(.004)	(.011)
total change in 2001-07	-.002	-.001	-.002	-.004	-.001
	(.003)	(.001)	(.002)	(.003)	(.008)
total change in 2007-11	-.007	-.003	-.006	-.012**	-.004
	(.004)	(.002)	(.003)	(.004)	(.013)

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 400 replications.

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

Table 3: *Decomposing inequality changes (in % points) between 2001 and 2007*

	Gini	Atkinson (0.5)	Atkinson (1)	Atkinson (2)	CV
total change	-.002	-.001	-.002	-.004	-.001
	(.003)	(.001)	(.002)	(.003)	(.008)
PCMI effect	.010***	.004***	.009***	.016***	.019*
	(.003)	(.001)	(.002)	(.003)	(.008)
iv) changes to wages	.005	.002	.004	.008	.006
	(.005)	(.002)	(.004)	(.006)	(.012)
v) changes to returns to HE: wBm	-.001	-.000	-.000	-.001	-.001
	(.001)	(.000)	(.001)	(.001)	(.002)
vi) changes to returns to HE: nwBm	-.000	-.000	-.000	-.001	-.001
	(.001)	(.000)	(.001)	(.001)	(.002)
vii) changes to returns to HE: wBf	-.001*	-.000	-.001	-.001*	-.002
	(.001)	(.000)	(.000)	(.001)	(.001)
viii) changes to returns to HE: nwBf	.000	.000	.000	.001	.001
	(.001)	(.000)	(.000)	(.001)	(.001)
ix) changes to education composition	.007***	.003***	.006***	.010***	.015***
	(.001)	(.000)	(.001)	(.001)	(.003)
x) residual	.000	.000	.000	.000	.002
	(.005)	(.002)	(.004)	(.006)	(.014)
TBP effect	-.013***	-.005***	-.010***	-.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 400 replications.

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

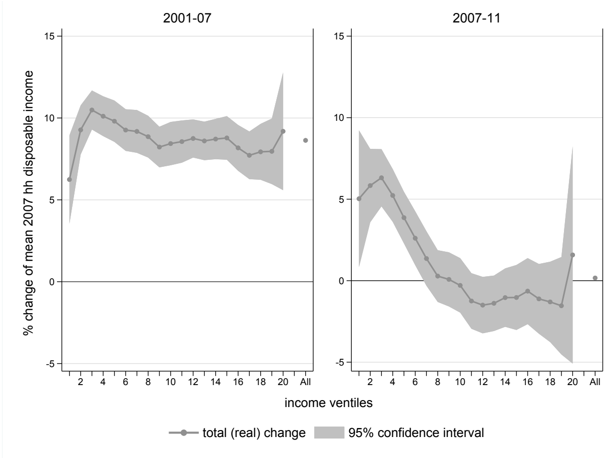
Table 4: *Decomposing inequality changes (in % points) between 2007 and 2011*

	Gini	Atkinson (0.5)	Atkinson (1)	Atkinson (2)	CV
total change	-.007	-.003	-.006	-.012**	-.004
	(.004)	(.002)	(.003)	(.004)	(.013)
PCMI effect	.001	.001	.001	-.002	.015
	(.004)	(.002)	(.003)	(.004)	(.013)
iv) changes to wages	.003	.002	.002	.002	.015
	(.004)	(.002)	(.003)	(.005)	(.012)
v) changes to returns to HE: wBm	.001	.000	.001	.001	.002
	(.001)	(.001)	(.001)	(.001)	(.003)
vi) changes to returns to HE: nwBm	.000	.000	.000	.001	.001
	(.001)	(.000)	(.001)	(.001)	(.002)
vii) changes to returns to HE: wBf	.001	.000	.001	.001	.002
	(.001)	(.000)	(.001)	(.001)	(.002)
viii) changes to returns to HE: nwBf	-.000	-.000	-.000	-.000	-.001
	(.001)	(.000)	(.001)	(.001)	(.002)
ix) changes to education composition	.002	.001	.002	.003	.004
	(.001)	(.001)	(.001)	(.002)	(.004)
x) residual	-.006	-.002	-.005	-.009	-.009
	(.004)	(.002)	(.003)	(.005)	(.013)
TBP effect	-.008***	-.003***	-.006***	-.011***	-.019***
	(.000)	(.000)	(.000)	(.001)	(.002)

Notes and Source: see Table 3

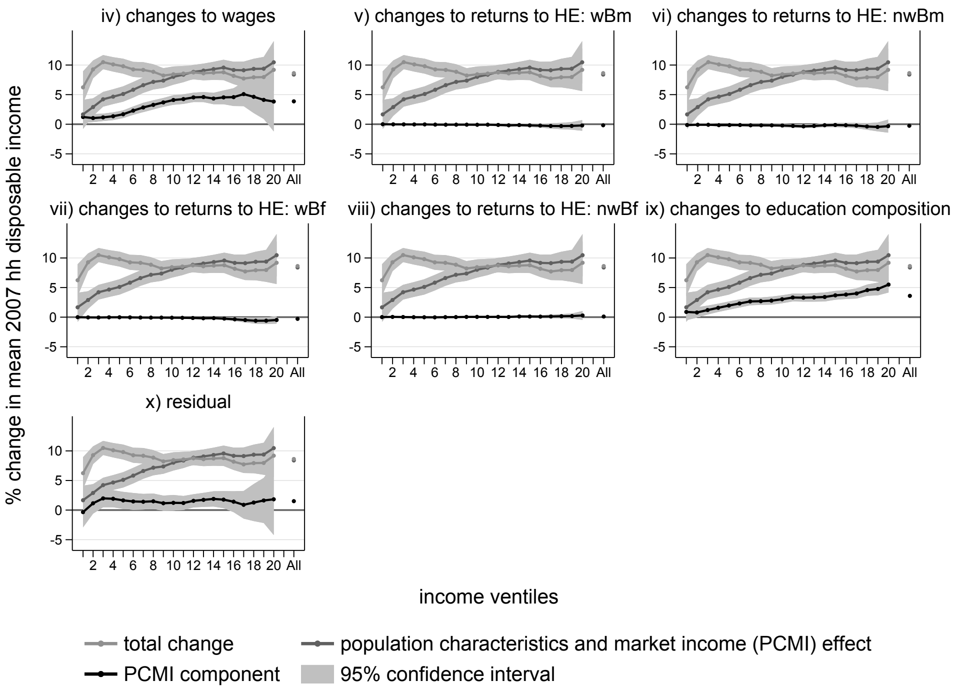
Figures

Figure 1: *Change in mean incomes between 2001 and 2007 and 2007 and 2011*



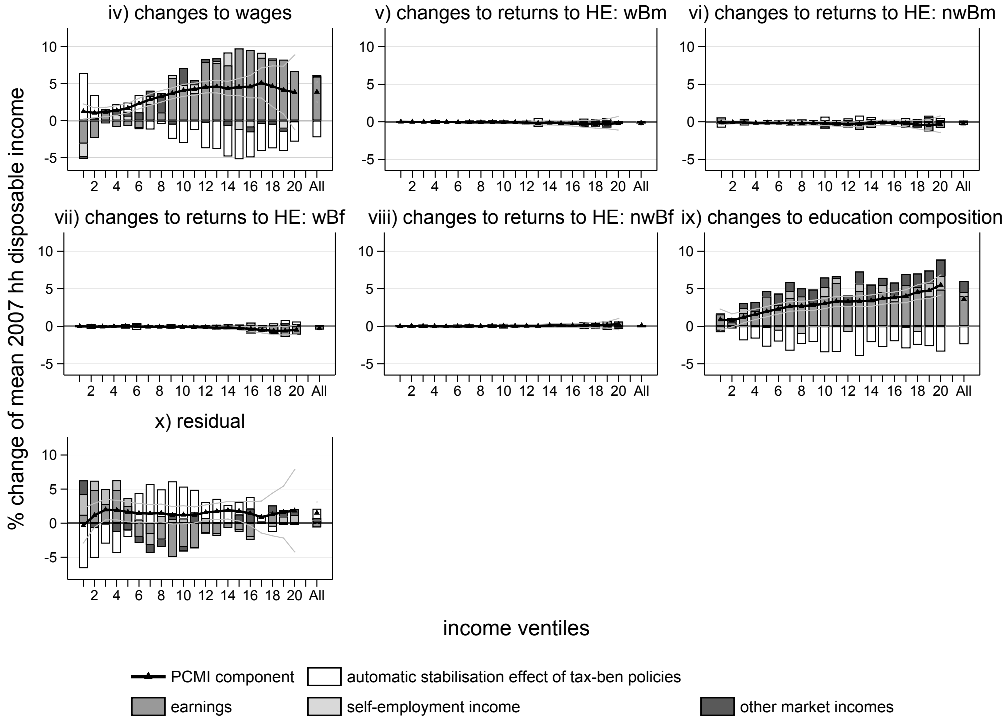
Notes: Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (2001/2007/2011 actual) distribution of equivalised household net income. Confidence intervals are estimated after 400 bootstrap replications.
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Figure 2: *Decomposing the change in mean incomes between 2001 and 2007*



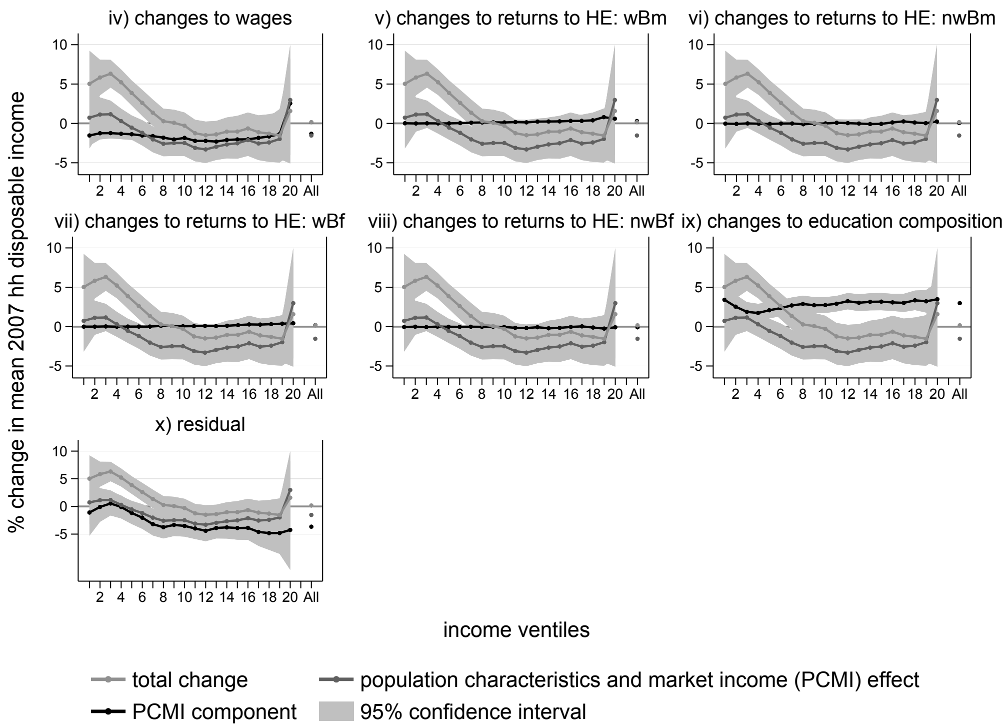
Notes: HE=higher education; wBm=white British males; nwBm=non-white-British males; wBf=white British females; nwBf=non-white-British females. The light and dark grey lines are the same in all subfigures. The black lines add up to the dark grey line. Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (actual or counterfactual) distribution of equivalised household net income. Confidence intervals are estimated after 400 bootstrap replications.
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Figure 3: *Decomposing the change in mean incomes (by income type) due to changes in PCMI, between 2001 and 2007*



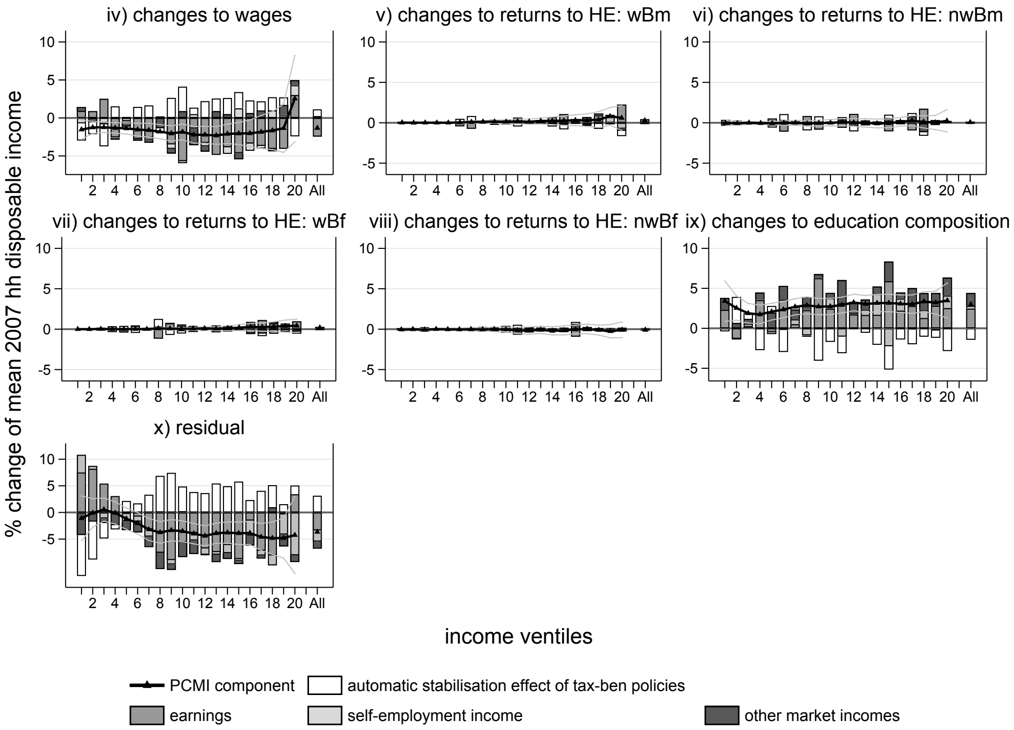
Notes: HE=higher education; wBm=white British males; nwBm=non-white-British males; wBf=white British females; nwBf=non-white-British females. The bars add up to the black line in each subfigure. Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (actual or counterfactual) distribution of equivalised household net income. Confidence intervals around PCMI component (grey lines) are estimated after 400 bootstrap replications.
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Figure 4: *Decomposing the change in mean incomes between 2007 and 2011*



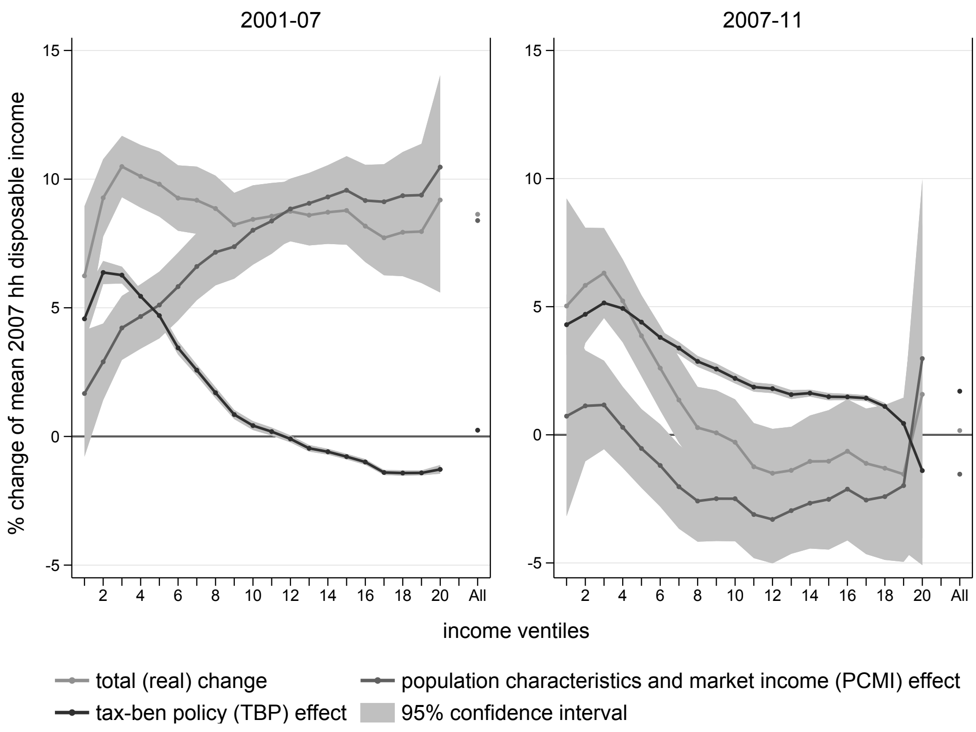
Notes and Source: see Figure 2.

Figure 5: *Decomposing the change in mean incomes (by income type) due to changes in PCMI between 2007 and 2011*



Notes and Source: see Figure 3.

Figure 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. Changes to incomes are estimated in real terms. Household ranking is not fixed and is based on the respective (actual or counterfactual) distribution of equivalised household net income. Confidence intervals are estimated after 400 bootstrap replications.
Source: Author's calculations using EUROMOD and the Family Resources Survey.

Supplementary materials

A Counterfactual wages

In term iv) of equation 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 $t = 1$:

$$\begin{aligned}
\ln \hat{y}^{wBm}_{i(h)} &= x^{wBm}_{i(h1)}\hat{\beta}_0 + e^{wBm}_{i(h1)}\hat{\lambda}_1 + \hat{\epsilon}_{i(h1)} * \frac{\sigma(\hat{\epsilon}_{i(h0)})}{\sigma(\hat{\epsilon}_{i(h1)})} \\
\ln \hat{y}^{nwBm}_{i(h)} &= x^{nwBm}_{i(h1)}\hat{\gamma}_0 + e^{nwBm}_{i(h1)}\hat{\delta}_1 + \hat{\eta}_{i(h1)} * \frac{\sigma(\hat{\eta}_{i(h0)})}{\sigma(\hat{\eta}_{i(h1)})} \\
\ln \hat{y}^{wBf}_{i(h)} &= x^{wBf}_{i(h1)}\hat{\pi}_0 + e^{wBf}_{i(h1)}\hat{\nu}_1 + \hat{\mu}_{i(h1)} * \frac{\sigma(\hat{\mu}_{i(h0)})}{\sigma(\hat{\mu}_{i(h1)})} \\
\ln \hat{y}^{nwBf}_{i(h)} &= x^{nwBf}_{i(h1)}\hat{\rho}_0 + e^{nwBf}_{i(h1)}\hat{\theta}_1 + \hat{\upsilon}_{i(h1)} * \frac{\sigma(\hat{\upsilon}_{i(h0)})}{\sigma(\hat{\upsilon}_{i(h1)})}
\end{aligned} \tag{A.1}$$

In terms v) to viii) of equation 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:

$$\begin{aligned}
\ln \hat{y}^{wBm}_{i(h)} &= x^{wBm}_{i(h1)}\hat{\beta}_0 + e^{wBm}_{i(h1)}\hat{\lambda}_0 + \hat{\epsilon}_{i(h1)} * \frac{\sigma(\hat{\epsilon}_{i(h0)})}{\sigma(\hat{\epsilon}_{i(h1)})} \\
\ln \hat{y}^{nwBm}_{i(h)} &= x^{nwBm}_{i(h1)}\hat{\gamma}_0 + e^{nwBm}_{i(h1)}\hat{\delta}_0 + \hat{\eta}_{i(h1)} * \frac{\sigma(\hat{\eta}_{i(h0)})}{\sigma(\hat{\eta}_{i(h1)})} \\
\ln \hat{y}^{wBf}_{i(h)} &= x^{wBf}_{i(h1)}\hat{\pi}_0 + e^{wBf}_{i(h1)}\hat{\nu}_0 + \hat{\mu}_{i(h1)} * \frac{\sigma(\hat{\mu}_{i(h0)})}{\sigma(\hat{\mu}_{i(h1)})} \\
\ln \hat{y}^{nwBf}_{i(h)} &= x^{nwBf}_{i(h1)}\hat{\rho}_0 + e^{nwBf}_{i(h1)}\hat{\theta}_0 + \hat{\upsilon}_{i(h1)} * \frac{\sigma(\hat{\upsilon}_{i(h0)})}{\sigma(\hat{\upsilon}_{i(h1)})}
\end{aligned} \tag{A.2}$$

B Data

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.[7] Therefore, this is the main variable we use in the paper. The variable has been used by other economists (Brewer and Wren-Lewis, 2015; Blundell et al., 2018).

The variable 'tea' has missing values for a small proportion of the sample: 5.3% in 2001/02, 6.2% in 2007/08 and 4.5% in 2011/12 among those aged 15-64. To fill in the missing values, we use information on age at the time of interview and the variable 'fted' (whether presently in full-time education).[8] In 2001/02 and 2007/08 waves, everyone with missing information for 'tea' has answered that they are in full-time education. This is also the case in 2011/12, apart from 101 cases (0.4%) who have answered that they are not in full-time education and have missing value for 'tea'. As a result, they are not classified in any of our education categories.

Table B.1 compares the FRS education distribution to the LFS education distribution. Although we do not measure directly education level, those with HE are most likely to be in our education category 'completed education aged 20+'. We compare this category with the published LFS statistics. Table B.1 shows that the FRS has lower levels of HE than the LFS data in all years. Both sources show a substantial increase in education attainment, although the trends differ somewhat by period: in 2001-07 LFS shows a 2.8 percentage points (pp) increase vs 4.3pp in FRS; and 4.5pp increase in LFS vs 2.3pp in FRS in 2007-11. This comparison suggests that, relative to using LFS data, 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; for the 2007-11 period our results may be underestimated. 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 B.2 and Table B.3 compare our education variable with these alternative variables where possible. In contrast to the LFS validation, these

[7] 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 the sample of those aged 15-64.

[8] For those aged 16 or less we assume that they are in education if with missing information.

both give closer estimates of the share with degree compared to the variable we use in the paper: 30.3% with FRS (our education variable) vs 28.6% with alternative FRS in 2007 (Table B.2); and 32.2% with FRS vs 29.8% with alternative FRS in 2011 (Table B.3). This comparison suggests that our FRS education variable is of good quality relative to alternative education definitions.

Table B.1: *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	20.2	24.5	26.8	4.3	2.3

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 who completed full-time education aged 20+. Sample is based on individuals aged 15-64.
Source: LFS statistics: Eurostat website, indicator edat_lfse_03, based on the Labour Force Survey.

Table B.2: *Share of individuals by education attainment in 2007*

	FRS	alternative FRS
not university	69.7	71.4
university	30.3	28.6

Notes: FRS: individuals are sorted into category 'not university' if completed full-time education aged <=19; and category 'university' if completed full-time education aged 20+. Alternative FRS: 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 B.3: *Share of individuals by education attainment in 2011*

	FRS	alternative FRS
secondary	36.2	41.0
college	31.5	29.2
university	32.2	29.8

Notes: FRS: individuals are sorted into category 'secondary' if completed full-time education aged <=16; category 'college' if completed full-time education aged 17-19; and category 'university' if completed full-time education aged 20+. Alternative FRS: 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:

+ **gross (pre-tax) market incomes**: 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;

+ **pensions**: retirement pension, occupational pension, war pension, widow pension;

+ **means-tested benefits and tax credits**: 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, income-based jobseeker's allowance;

+ **non-means-tested benefits**: contributory jobseeker's allowance, student payments, student loans, attendance allowance, disability living allowance, disability living (mobility) allowance, incapacity benefit, contributory employment and support allowance, industrial injuries pension, invalid care allowance, severe disablement allowance, statutory sick pay, training allowance, statutory maternity pay, maternity allowance, winter fuel allowance, child benefit, 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 the bottom 4% and top 1% of the net income distribution and by dropping Northern Ireland from the 2007/08 and 2011/12 waves. Table B.4 shows sample sizes before and after the sample restrictions we impose on the FRS data:

Table B.4: *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.

C Comparing income statistics based on simulated vs reported incomes

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.[9] We expect that these differences in the income definition will not cause large discrepancies between the two income distributions.

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

[9] 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.

throughout the financial year.[10] 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.[11]

Table C.1 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 C.1 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 C.1 is that the results for the changes in the income statistics based on both simulated and reported incomes are of very similar magnitude, with 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

[10] 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.

[11] 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.

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).

Table C.1: *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 2007-11	2001/02	2007/08	2011/12	% Δ in 2001-07	% Δ in 2007-11	Δ in 2001-07	Δ in 2007-11
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 1,000 replications.
Source: Authors' calculations using EUROMOD and the Family Resources Survey.

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 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.

D OLS regression results

This appendix presents the model specification for wages and the OLS regression results. In the wage models, education level (completed full-time education aged 16 or less, aged 17-19, aged 20+) 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 age, being in a couple, age group (in 5-year bands), number of hours worked (in bands), 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 D.1 and Table D.2 present the OLS regression results for 2001 and 2007 for males and females, respectively. Table D.3 and Table D.4 show the OLS regression results for 2007 and 2011 male and female workers, respectively.

Table D.1: *OLS log-earnings estimation results for males in 2001 and 2007*

	2001 wB	2007 wB	2001 nwB	2007 nwB
Constant	7.697***	7.831***	7.366***	7.538***
	(.056)	(.071)	(.187)	(.166)
Children in the household: none (ref)				
1	-.059**	-.034	-.045	-.012
	(.020)	(.022)	(.064)	(.061)
2	-.010	-.000	.038	-.018
	(.023)	(.028)	(.094)	(.079)
3+	-.041	-.015	-.224*	-.152
	(.031)	(.042)	(.092)	(.096)
Adults in the household: 1 (ref)				
2	-.021	.013	.196	.103
	(.031)	(.031)	(.108)	(.066)
3+	-.021	.025	.095	.039
	(.028)	(.030)	(.114)	(.072)
Head of the household	.402***	.423***	.483***	.338***
	(.016)	(.021)	(.064)	(.043)
Average age in the household	-.003**	-.003*	.001	.003
	(.001)	(.001)	(.004)	(.004)
In a couple	.157***	.146***	.071	.093
	(.028)	(.029)	(.104)	(.052)
Working hours: 50+ (ref)				
1-29	-1.195***	-1.237***	-1.387***	-1.442***
	(.054)	(.057)	(.095)	(.086)
30-39	-.086***	-.138***	-.111	-.283***
	(.015)	(.024)	(.066)	(.061)
40-49	-.127***	-.139***	-.113	-.235***
	(.015)	(.023)	(.067)	(.057)
Age: 40-44 (ref)				
25-29	-.297***	-.296***	-.809**	-.345**
	(.029)	(.032)	(.309)	(.116)
30-34	-.214***	-.263***	-.286**	-.332*
	(.024)	(.031)	(.090)	(.135)
35-39	-.186***	-.253***	-.364***	-.301**
	(.021)	(.030)	(.096)	(.104)
45-49	-.128***	-.177***	-.214	-.122
	(.023)	(.026)	(.120)	(.124)
50-54	-.142***	-.200***	-.300*	-.347***
	(.025)	(.029)	(.122)	(.087)
55-59	-.193***	-.240***	-.400	.023
	(.030)	(.038)	(.238)	(.157)
60-64	-.315***	-.312***	-.557***	-.121
	(.035)	(.040)	(.142)	(.213)
Aged 40-45 & completed education aged 16 or less (ref)				
age 25-29 & completed education aged 17-19	.087**	.056	.620	.056
	(.030)	(.038)	(.325)	(.127)
age 30-34 & completed education aged 17-19	.146***	.096*	.033	.131
	(.028)	(.040)	(.091)	(.139)
age 35-39 & completed education aged 17-19	.245***	.216***	.208	.148
	(.036)	(.040)	(.137)	(.115)
age 45-49 & completed education aged 17-19	.212***	.228***	.174	.148
	(.036)	(.038)	(.174)	(.143)
age 50-54 & completed education aged 17-19	.232***	.269***	-.068	.222
	(.047)	(.048)	(.194)	(.173)
age 55-59 & completed education aged 17-19	.220**	.336***	.591	-.017
	(.077)	(.059)	(.351)	(.237)
age 60-64 & completed education aged 17-19	.245**	.308***	.242	.619*
	(.093)	(.084)	(.263)	(.279)
age 30-34 & completed education aged 20+	.282***	.185***	.854**	.294*
	(.035)	(.036)	(.322)	(.118)
age 30-34 & completed education aged 20+	.438***	.354***	.442***	.466***
	(.037)	(.035)	(.097)	(.130)
age 35-39 & completed education aged 20+	.547***	.542***	.474***	.421***
	(.038)	(.043)	(.116)	(.115)
age 45-49 & completed education aged 20+	.523***	.467***	.370**	.210
	(.050)	(.062)	(.135)	(.154)
age 50-54 & completed education aged 20+	.534***	.610***	.031	.518***
	(.043)	(.081)	(.213)	(.150)
age 55-59 & completed education aged 20+	.470***	.533***	.349	.302
	(.062)	(.068)	(.276)	(.248)
age 60-64 & completed education aged 20+	.400	.361**	.578***	.028
	(.206)	(.139)	(.154)	(.283)
Region: London (ref)				
North East	-.360***	-.323***	-.102	-.194
	(.032)	(.040)	(.155)	(.247)
North West	-.305***	-.342***	-.324***	-.241***
	(.026)	(.036)	(.076)	(.059)
Yorks and Humberside	-.350***	-.374***	-.174	-.171*
	(.026)	(.036)	(.113)	(.070)
East Midlands	-.296***	-.330***	-.128	-.366***
	(.025)	(.034)	(.102)	(.061)
West Midlands	-.280***	-.337***	-.256***	-.218**

	(.026)	(.036)	(.064)	(.067)
Eastern	-.144***	-.242***	.014	-.042
	(.025)	(.036)	(.096)	(.066)
South East	-.061*	-.142***	.074	-.115*
	(.025)	(.034)	(.059)	(.058)
South West	-.299***	-.308***	-.224*	-.161*
	(.026)	(.035)	(.105)	(.080)
Wales	-.381***	-.392***	-.252*	-.236*
	(.032)	(.039)	(.116)	(.113)
Scotland	-.309***	-.277***	-.648	-.123
	(.026)	(.032)	(.392)	(.067)
R-squared	.379	.349	.380	.425
N	9,012	7,572	963	1,164

Notes: *wB*=white British and *nwB*=non-white-British. Significance levels indicated as $*\ \ p < 0.1$, $**\ \ p < 0.05$, $***\ \ p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 400 replications. *Source:* Author's calculations using the Family Resources Survey.

Table D.2: *OLS log-earnings estimation results for females in 2001 and 2007*

	2001 wB	2007 wB	2001 nwB	2007 nwB
Constant	7.229***	7.589***	7.264***	7.244***
	(.085)	(.065)	(.221)	(.198)
Children in the household: none (ref)				
1	-.085**	-.066**	-.078	-.020
	(.030)	(.022)	(.065)	(.071)
2	-.073**	-.049	-.083	-.003
	(.026)	(.027)	(.091)	(.089)
3+	-.152***	-.050	-.038	.136
	(.038)	(.051)	(.109)	(.133)
Adults in the household: 1 (ref)				
2	.016	-.021	-.099	-.020
	(.024)	(.026)	(.087)	(.074)
3+	-.042	-.083**	-.117	-.002
	(.025)	(.027)	(.088)	(.076)
Head of the household	.318***	.311***	.250***	.383***
	(.019)	(.017)	(.052)	(.047)
Average age in the household	.002	-.002*	.003	.003
	(.001)	(.001)	(.004)	(.004)
In a couple	.221***	.251***	.132	.086
	(.019)	(.021)	(.073)	(.061)
Working hours: 40+ (ref)				
1-15	-1.599***	-1.595***	-1.679***	-1.445***
	(.027)	(.036)	(.105)	(.105)
16-29	-.763***	-.800***	-.863***	-.734***
	(.020)	(.022)	(.081)	(.058)
30-39	-.086***	-.091***	-.025	-.073
	(.018)	(.018)	(.047)	(.051)
Age: 40-44 (ref)				
25-29	-.177***	-.194***	-.121	-.346**
	(.033)	(.038)	(.114)	(.129)
30-34	-.227**	-.264***	-.093	-.204
	(.075)	(.036)	(.117)	(.170)
35-39	-.136***	-.224***	-.203	-.039
	(.025)	(.029)	(.147)	(.105)
45-49	-.182***	-.163***	-.197*	-.108
	(.025)	(.029)	(.097)	(.101)
50-54	-.249***	-.193***	-.282*	-.179
	(.025)	(.034)	(.139)	(.103)
55-59	-.305***	-.218***	-.363**	-.125
	(.033)	(.034)	(.134)	(.137)
Aged 40-45 & completed education aged 16 or less (ref)				
age 25-29 & completed education aged 17-19	.138***	.010	.019	.306*
	(.036)	(.049)	(.112)	(.137)
age 30-34 & completed education aged 17-19	.290***	.160***	.021	.278
	(.085)	(.043)	(.104)	(.175)
age 35-39 & completed education aged 17-19	.227***	.223***	.237	.028
	(.030)	(.040)	(.144)	(.099)
age 45-49 & completed education aged 17-19	.216***	.233***	-.045	.192
	(.033)	(.035)	(.135)	(.112)
age 50-54 & completed education aged 17-19	.248***	.173***	.152	.345**
	(.049)	(.047)	(.146)	(.119)
age 55-59 & completed education aged 17-19	.264***	.208***	.238	-.019
	(.055)	(.048)	(.146)	(.146)
age 30-34 & completed education aged 20+	.381***	.236***	.198*	.350*
	(.038)	(.039)	(.089)	(.137)
age 30-34 & completed education aged 20+	.637***	.564***	.327**	.495**
	(.090)	(.043)	(.107)	(.161)
age 35-39 & completed education aged 20+	.588***	.599***	.369*	.289*
	(.063)	(.052)	(.160)	(.112)
age 45-49 & completed education aged 20+	.654***	.567***	.271*	.262

	(.046)	(.054)	(.110)	(.148)
age 50-54 & completed education aged 20+	.588***	.524***	.178	.307
	(.051)	(.052)	(.154)	(.163)
age 55-59 & completed education aged 20+	.610***	.563***	.440	.117
	(.068)	(.058)	(.251)	(.159)
Region: London (ref)				
North East	-.286***	-.303***	.060	-.217*
	(.070)	(.036)	(.136)	(.097)
North West	-.251***	-.319***	-.238**	-.262*
	(.066)	(.033)	(.086)	(.111)
Yorks and Humberside	-.249***	-.322***	-.178	-.102
	(.068)	(.034)	(.097)	(.110)
East Midlands	-.234***	-.305***	-.230*	-.389***
	(.070)	(.035)	(.094)	(.068)
West Midlands	-.270***	-.287***	-.085	-.242**
	(.069)	(.038)	(.070)	(.078)
Eastern	-.153*	-.258***	-.003	-.003
	(.066)	(.035)	(.078)	(.072)
South East	-.138*	-.164***	-.033	-.121*
	(.064)	(.033)	(.067)	(.059)
South West	-.269***	-.312***	-.061	-.356***
	(.070)	(.037)	(.096)	(.099)
Wales	-.291***	-.415***	-.234	-.303***
	(.068)	(.041)	(.157)	(.089)
Scotland	-.247***	-.289***	-.043	-.216***
	(.064)	(.030)	(.192)	(.060)
R-squared	.471	.550	.532	.453
N	8,583	7,221	851	1,023

Notes: *wB*=white British and *nwB*=non-white-British. Significance levels indicated as $*\ \ p < 0.1$, $**\ \ p < 0.05$, $***\ \ p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 400 replications.
Source: Author's calculations using the Family Resources Survey.

Table D.3: *OLS log-earnings estimation results for males in 2007 and 2011*

	2007 wB	2011 wB	2007 nwB	2011 nwB
Constant	7.930***	7.881***	7.636***	7.747***
	(.071)	(.086)	(.166)	(.191)
Children in the household: none (ref)				
1	-.034	-.005	-.012	.043
	(.022)	(.028)	(.061)	(.060)
2	-.000	.044	-.018	.079
	(.028)	(.043)	(.079)	(.078)
3+	-.015	.022	-.152	-.245*
	(.042)	(.047)	(.096)	(.109)
Adults in the household: 1 (ref)				
2	.013	.092*	.103	-.051
	(.031)	(.045)	(.066)	(.102)
3+	.025	.061	.039	-.164
	(.030)	(.041)	(.072)	(.094)
Head of the household	.423***	.401***	.338***	.373***
	(.021)	(.035)	(.043)	(.052)
Average age in the household	-.003*	-.003*	.003	.002
	(.001)	(.001)	(.004)	(.004)
In a couple	.146***	.071	.093	.069
	(.029)	(.039)	(.052)	(.064)
Working hours: 50+ (ref)				
1-29	-1.237***	-1.206***	-1.442***	-1.411***
	(.057)	(.059)	(.086)	(.090)
30-39	-.138***	-.185***	-.283***	-.300***
	(.024)	(.027)	(.061)	(.076)
40-49	-.139***	-.179***	-.235***	-.230**
	(.023)	(.028)	(.057)	(.071)
Age: 40-44 (ref)				
25-29	-.296***	-.394***	-.345**	-.618**
	(.032)	(.054)	(.116)	(.191)
30-34	-.263***	-.375***	-.332*	-.307*
	(.031)	(.037)	(.135)	(.119)
35-39	-.253***	-.228***	-.301**	-.391***
	(.030)	(.040)	(.104)	(.107)
45-49	-.177***	-.104**	-.122	-.166
	(.026)	(.032)	(.124)	(.110)
50-54	-.200***	-.118**	-.347***	-.033
	(.029)	(.036)	(.087)	(.117)
55-59	-.240***	-.144***	.023	-.240
	(.038)	(.040)	(.157)	(.158)
60-64	-.312***	-.238***	-.121	-.332*
	(.040)	(.044)	(.213)	(.147)
Aged 40-45 & completed education aged 16 or less (ref)				

age 25-29 & completed education aged 17-19	.056	.053	.056	.390*
	(.038)	(.060)	(.127)	(.187)
age 30-34 & completed education aged 17-19	.096*	.193***	.131	-.074
	(.040)	(.047)	(.139)	(.110)
age 35-39 & completed education aged 17-19	.216***	.124*	.148	.131
	(.040)	(.053)	(.115)	(.127)
age 45-49 & completed education aged 17-19	.228***	.191***	.148	.147
	(.038)	(.049)	(.143)	(.138)
age 50-54 & completed education aged 17-19	.269***	.279***	.222	-.056
	(.048)	(.060)	(.173)	(.134)
age 55-59 & completed education aged 17-19	.336***	.280***	-.017	.056
	(.059)	(.058)	(.237)	(.202)
age 60-64 & completed education aged 17-19	.308***	.045	.619*	.169
	(.084)	(.110)	(.279)	(.155)
age 30-34 & completed education aged 20+	.185***	.302***	.294*	.556**
	(.036)	(.056)	(.118)	(.183)
age 30-34 & completed education aged 20+	.354***	.534***	.466***	.291**
	(.035)	(.050)	(.130)	(.111)
age 35-39 & completed education aged 20+	.542***	.563***	.421***	.531***
	(.043)	(.095)	(.115)	(.111)
age 45-49 & completed education aged 20+	.467***	.436***	.210	.422**
	(.062)	(.069)	(.154)	(.147)
age 50-54 & completed education aged 20+	.610***	.564***	.518***	.017
	(.081)	(.069)	(.150)	(.237)
age 55-59 & completed education aged 20+	.533***	.423***	.302	.101
	(.068)	(.069)	(.248)	(.183)
age 60-64 & completed education aged 20+	.361**	.482***	.028	.217
	(.139)	(.106)	(.283)	(.253)
Region: London (ref)				
North East	-.323***	-.415***	-.194	-.208
	(.040)	(.056)	(.247)	(.114)
North West	-.342***	-.299***	-.241***	-.215**
	(.036)	(.046)	(.059)	(.073)
Yorks and Humberside	-.374***	-.329***	-.171*	-.174
	(.036)	(.048)	(.070)	(.091)
East Midlands	-.330***	-.364***	-.366***	-.136
	(.034)	(.051)	(.061)	(.079)
West Midlands	-.337***	-.315***	-.218**	-.322***
	(.036)	(.047)	(.067)	(.075)
Eastern	-.242***	-.174**	-.042	-.165*
	(.036)	(.064)	(.066)	(.068)
South East	-.142***	-.169***	-.115*	.060
	(.034)	(.049)	(.058)	(.068)
South West	-.308***	-.266***	-.161*	-.111
	(.035)	(.048)	(.080)	(.103)
Wales	-.392***	-.378***	-.236*	-.063
	(.039)	(.057)	(.113)	(.115)
Scotland	-.277***	-.256***	-.123	-.124
	(.032)	(.044)	(.067)	(.087)
R-squared	.349	.346	.425	.462
N	7,572	5,915	1,164	1,104

Notes: *wB*=white British and *nwB*=non-white-British. Significance levels indicated as $*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 400 replications.
Source: Author's calculations using the Family Resources Survey.

Table D.4: *OLS log-earnings estimation results for females in 2007 and 2011*

	2007 wB	2011 wB	2007 nwB	2011 nwB
Constant	7.688***	7.472***	7.343***	7.368***
	(.065)	(.082)	(.198)	(.188)
Children in the household: none (ref)				
1	-.066**	-.097***	-.020	-.049
	(.022)	(.026)	(.071)	(.064)
2	-.049	-.006	-.003	-.125
	(.027)	(.042)	(.089)	(.097)
3+	-.050	-.235***	.136	-.033
	(.051)	(.053)	(.133)	(.132)
Adults in the household: 1 (ref)				
2	-.021	.065	-.020	.073
	(.026)	(.036)	(.074)	(.100)
3+	-.083**	.007	-.002	-.056
	(.027)	(.037)	(.076)	(.096)
Head of the household	.311***	.364***	.383***	.345***
	(.017)	(.027)	(.047)	(.048)
Average age in the household	-.002*	-.000	.003	.002
	(.001)	(.002)	(.004)	(.004)
In a couple	.251***	.239***	.086	.140*
	(.021)	(.027)	(.061)	(.065)

Working hours: 40+ (ref)				
1-15	-1.595***	-1.495***	-1.445***	-1.502***
	(.036)	(.045)	(.105)	(.122)
16-29	-.800***	-.763***	-.734***	-.854***
	(.022)	(.035)	(.058)	(.069)
30-39	-.091***	-.060*	-.073	-.075
	(.018)	(.024)	(.051)	(.052)
Age: 40-44 (ref)				
25-29	-.194***	-.349***	-.346**	-.370
	(.038)	(.060)	(.129)	(.285)
30-34	-.264***	-.300***	-.204	-.140
	(.036)	(.064)	(.170)	(.136)
35-39	-.224***	-.189***	-.039	-.316**
	(.029)	(.043)	(.105)	(.111)
45-49	-.163***	-.237***	-.108	.043
	(.029)	(.041)	(.101)	(.143)
50-54	-.193***	-.213***	-.179	-.416**
	(.034)	(.040)	(.103)	(.130)
55-59	-.218***	-.346***	-.125	-.182
	(.034)	(.093)	(.137)	(.140)
Aged 40-45 & completed education aged 16 or less (ref)				
age 25-29 & completed education aged 17-19	.010	.118	.306*	-.112
	(.049)	(.061)	(.137)	(.321)
age 30-34 & completed education aged 17-19	.160***	.183**	.278	.036
	(.043)	(.067)	(.175)	(.152)
age 35-39 & completed education aged 17-19	.223***	.102*	.028	.395**
	(.040)	(.050)	(.099)	(.143)
age 45-49 & completed education aged 17-19	.233***	.210***	.192	-.060
	(.035)	(.037)	(.112)	(.158)
age 50-54 & completed education aged 17-19	.173***	.276***	.345**	.421**
	(.047)	(.044)	(.119)	(.145)
age 55-59 & completed education aged 17-19	.208***	.301**	-.019	-.021
	(.048)	(.105)	(.146)	(.167)
age 30-34 & completed education aged 20+	.236***	.330***	.350*	.187
	(.039)	(.057)	(.137)	(.291)
age 30-34 & completed education aged 20+	.564***	.548***	.495**	.211
	(.043)	(.062)	(.161)	(.152)
age 35-39 & completed education aged 20+	.599***	.504***	.289*	.546***
	(.052)	(.047)	(.112)	(.119)
age 45-49 & completed education aged 20+	.567***	.730***	.262	.195
	(.054)	(.052)	(.148)	(.180)
age 50-54 & completed education aged 20+	.524***	.564***	.307	.443**
	(.052)	(.062)	(.163)	(.165)
age 55-59 & completed education aged 20+	.563***	.703***	.117	.063
	(.058)	(.113)	(.159)	(.184)
Region: London (ref)				
North East	-.303***	-.279***	-.217*	-.210
	(.036)	(.051)	(.097)	(.189)
North West	-.319***	-.312***	-.262*	-.207**
	(.033)	(.066)	(.111)	(.076)
Yorks and Humberside	-.322***	-.257***	-.102	-.132
	(.034)	(.050)	(.110)	(.091)
East Midlands	-.305***	-.266***	-.389***	-.214*
	(.035)	(.050)	(.068)	(.087)
West Midlands	-.287***	-.207***	-.242**	-.362***
	(.038)	(.047)	(.078)	(.104)
Eastern	-.258***	-.133*	-.003	-.232**
	(.035)	(.066)	(.072)	(.083)
South East	-.164***	-.159***	-.121*	-.093
	(.033)	(.045)	(.059)	(.057)
South West	-.312***	-.278***	-.356***	-.359**
	(.037)	(.047)	(.099)	(.127)
Wales	-.415***	-.254***	-.303***	-.171
	(.041)	(.054)	(.089)	(.155)
Scotland	-.289***	-.196***	-.216***	-.115
	(.030)	(.044)	(.060)	(.112)
R-squared	.550	.390	.453	.461
N	7,221	5,809	1,023	955

Notes: wB=white British and nwB=non-white-British. Significance levels indicated as $*\ \ p < 0.1$, $**\ \ p < 0.05$, $***\ \ p < 0.01$ and standard errors shown in parentheses. Bootstrapped standard errors after 400 replications.
Source: Author's calculations using the Family Resources Survey.