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Scottish labour market trends 2019-22

Report summary

Purpose of report

This report summarizes trends in the labour market for those aged 16-64 using LFS data from 2019-2022. This is in preparation for using the Labour Force Survey (LFS) to update Family Resources Survey (FRS) data to provide a snapshot of household income, inequality, and poverty after the pandemic. To update the 2019-20 FRS data, we apply a reweighting matrix to the FRS data to match labour market characteristics in the first quarter of 2022. Reweighting is performed within groups defined by gender, age, and highest qualification achieved.

Summary of findings

- Employment and unemployment rates for men 25 and older with less than degree-level qualifications worsened during the pandemic and have not recovered, while men with degrees or higher education qualifications and most women have returned to pre-pandemic levels of employment.
- Weekly hours worked by those in employment fell during the pandemic and had recovered by the beginning of 2022.
- Real weekly pay remained mostly steady for those in employment through the pandemic, but began to fall towards the end of 2021 as inflation increased. This points to the efficacy of furlough schemes for maintaining income for those in employment, but does not say anything about the income of those that were unemployed or became inactive during the pandemic.

A summary of changes in the labour market between the first quarter of 2020 and 2022 is shown in Table 1. Statistics are grouped by gender, age group (16-49 and 50+), and level of qualification. Due to the small sample size, no differences are significant at the 95% level of confidence. Trends over the period 2019-2022 are discussed in more detail in the following report.

Table 1: Summary of labour market changes, 2020Q1-2022Q1

Age 16-49	Qualification	Δ Emp. rate	Δ Unemp. rate	Δ Hours	Δ Weekly pay (2019Q1 £)
Female	Degree or higher ed	5.28	-2.17	0.65	23.38
	Highers	2.62	-2.30	0.75	1.96
	Standard Grades, other, or less	1.39	-6.04	0.96	-51.91
Male	Degree or higher ed	3.88	-1.76	-0.04	31.79
	Highers	2.73	-0.60	3.17	-55.46
	Standard Grades, other, or less	-3.25	1.04	2.64	49.10
Age 50+					
Female	Degree or higher ed	0.94	0.41	0.71	41.16
	Highers	-5.25	0.98	6.92	-54.60
	Standard Grades, other, or less	3.91	-2.84	0.33	78.38
Male	Degree or higher ed	-1.07	1.43	1.34	-38.62
	Highers	-8.24	1.37	4.04	67.67
	Standard Grades, other, or less	-2.58	3.86	1.09	3.80

Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: Green indicates an improvement in 2022Q1 over 2020Q1, and red indicates a decline. No differences are statistically significant at the 95% level.

Data

The Labour Force Survey (LFS) is conducted on a quarterly basis by calendar quarters (e.g. Jan-Mar is Q1). The LFS questionnaire asks households about a wide range of labour force characteristics and related topics, including economic activity and employment status, hours, and pay. Individual and household data also contain respondents' demographic characteristics, including age, gender, and education level. The survey is nationally representative given the use of appropriate individual-level weights; all figures are weighted averages reflecting population-level estimates of key statistics. A one-year moving average is applied to all figures to account for seasonality unless otherwise noted.[1]

Overall labour market trends in Scotland and rUK

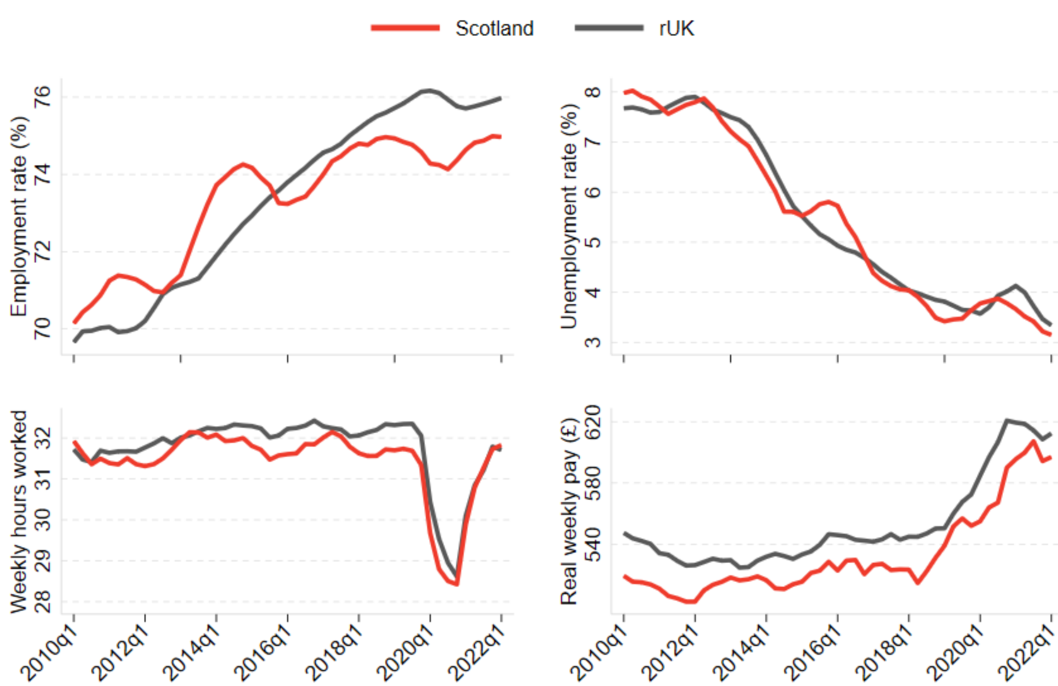

Figure 1: Employment trends in Scotland vs. rUK
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using a moving average to account for seasonality.

Overall trends in key labour market statistics are shown in Figure 1 for Scotland, benchmarked against the rest of the UK. Compared to just prior to the pandemic, the Scottish labour market has generally recovered in terms of employment and average hours worked per week, and seen improvements in real weekly pay and the unemployment rate. Employment rebounded faster in

[1] The Scottish Government applies their own seasonality adjustment; therefore, these charts may not match exactly with figures published in labour market reports.

Scotland than in the rest of the UK after hitting a low in 2020Q3, and remains approximately 1 percentage point (1pp) lower than the rest of the UK's rate. The employment rate has now resumed a general upward trend in both Scotland and rUK. Similarly, after a rise during the pandemic, unemployment has resumed a downward trend. Unemployment peaked in 2020Q3 for Scotland, at a lower rate than that for the rest of the UK, and has since fallen to about 0.6pp lower than the first quarter of 2020. Weekly hours worked by those in employment tracked closely with the rest of the UK through the pandemic dip and are now roughly comparable to pre-pandemic levels.

Finally, real weekly pay among employed people has trended upwards over the last four years after stagnating from 2010-2018. Analysis of trends in real pay during the pandemic is complicated by furlough effects and compositional effects. In Scotland as well as in the rest of the UK, workers returning to full pay after furlough drove some of the increase in the real wage in 2020-2021, as did a shift in the composition of the labour market towards higher-paying jobs earlier in the pandemic (Cominetti et al. 2022). The subsequent decline at the end of 2021 is likely due to a growing rate of inflation (Gillespie 2022).

Employment trends 2019-2022

Employment rates

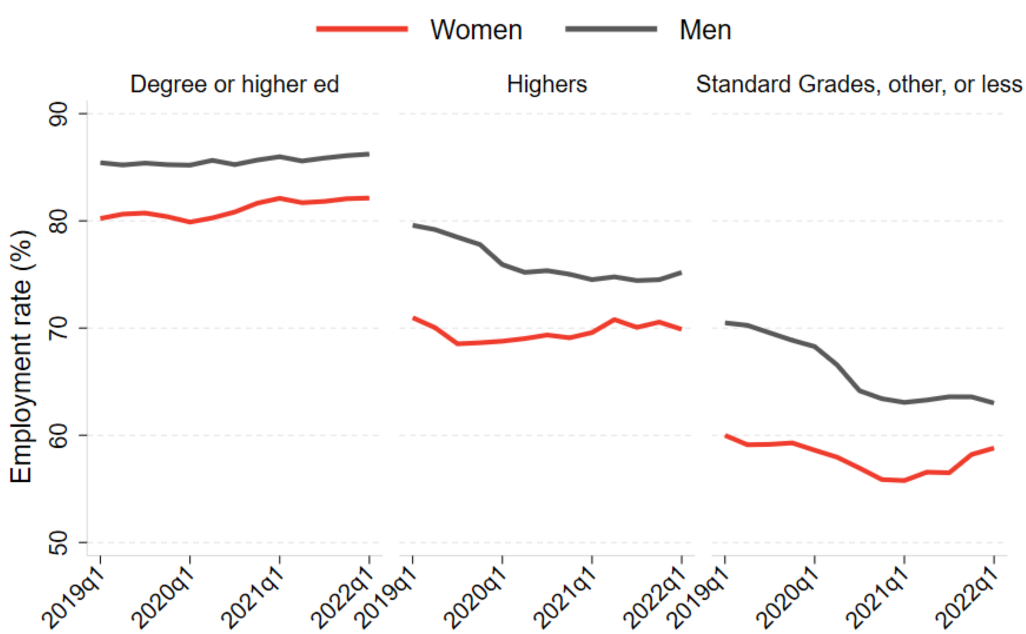

Figure 2: Employment rates by gender and qualification level
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

The employment rate is defined as the proportion of the total population aged 16-64 who are in paid work or temporarily not working (such as those on holiday or off sick). The overall employment rate in Scotland for those aged 16-64 ranged between 70-75% from 2010-2019, and 73-75% during the pandemic. Employment rates are typically lower for women, those under 24 or over 50, and those with lower educational credentials.

From 2019 to the first quarter of 2022, employment rates held relatively steady for those with degrees or higher education qualifications (Figure 2). Women with Higher qualifications or less had slight dips in employment which rebounded by the first quarter of 2022, while men with these qualifications have had persistently falling employment rates.

The persistence of reductions in employment for men with lower qualifications may be partially explained by the continuing impact of the pandemic on services and trade occupations (Figure 3). Trades, process and plant, services, sales, and elementary occupations made up 46.1% of employment in the first quarter of 2019; this number fell to 40.3% in the second quarter of 2020, and had increased to only 41.5% by the first quarter of 2022.

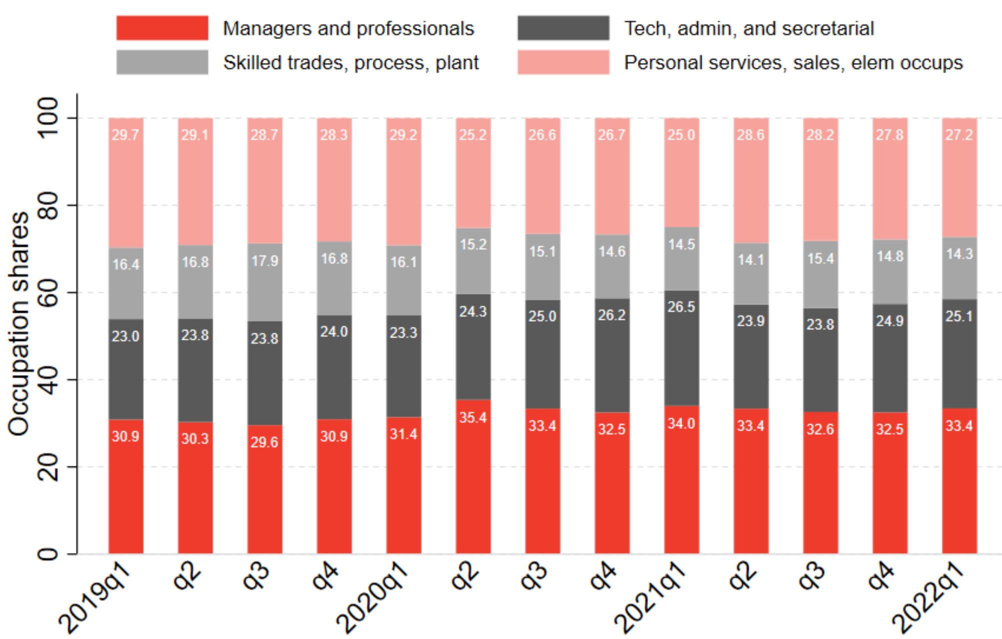

Figure 3: Shares of employment by occupation
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

Gendered patterns of employment are also apparent by age group (Figure 4). The employment of those aged 16-24 and men aged 25-49 was in decline going into the pandemic, possibly due to the return of employed immigrants to the EU during the Brexit transition. Employment rates for both men and women aged 16-24 had risen slightly above their level in the first quarter of 2019, and well above the rates in the first quarter of 2020.

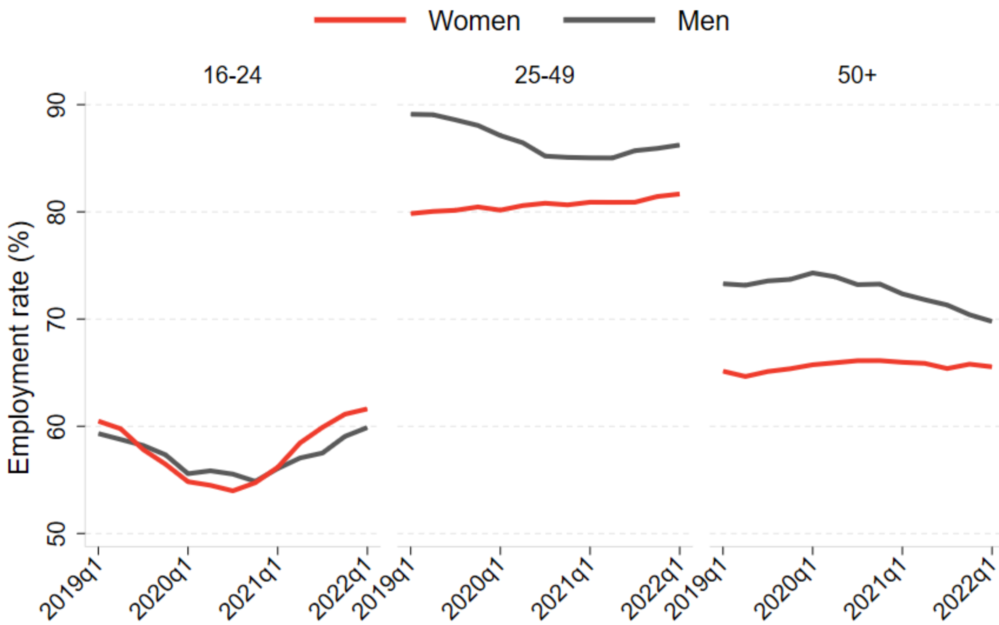

Figure 4: Employment rates by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

Men aged 25-49, however, have an employment rate that is still about 5pp lower than it was in the first quarter of 2019. For the over-50 population, men's employment declined from the start of the pandemic to the first quarter of 2022, while women's employment remained fairly level throughout. Men's activity rates followed the same patterns by age and qualification as did employment (see Figures A1-A2).

Unemployment

The unemployment rate refers to the proportion of the economically active population aged 16-64 that is not working, but is actively seeking work. In contrast to reports for the entire UK (Cribb et al. 2021, Bell et al. 2021), furlough schemes in Scotland were not entirely successful in holding unemployment down for all groups, although they did reduce unemployment from what it might have been (Gillespie 2020). In particular, younger people and those with lower levels of education saw rises in unemployment during the pandemic, and not all groups have fully recovered.

Unemployment rates varied widely through the pandemic period by qualification level (Figure 5), with relatively steady, low unemployment around 3% for those with degrees (particularly women) and more volatile patterns for other qualification levels. For those with Higher qualifications, unemployment rose during the first few quarters of the pandemic, but then fell back to roughly pre-pandemic levels. Men in this category have slightly lower unemployment then in the first quarter of 2019, and women have slightly higher unemployment. The most drastic change is for men with Standard Grade, other, or no qualifications. These men saw a sharp rise in unemployment from 2020Q1 to 2021Q1; their unemployment has started to decrease, but remains a little over 9%. On the other hand, women in this qualification category had higher unemployment during the pandemic but had returned to pre-pandemic levels of unemployment by the last quarter of 2021.

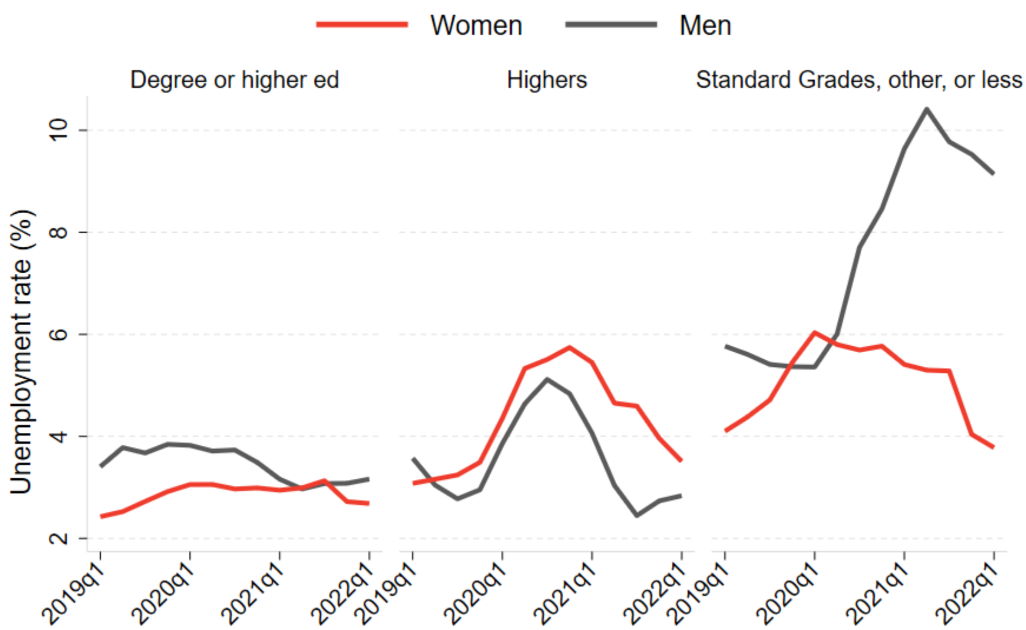

Figure 5: Unemployment by gender and qualification level
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

Changes in unemployment rates also varied by age group (Figure 6). Those aged 16-24 were most affected by the pandemic, with unemployment rates rising over 12% for both men and women. Men in this age group had a higher unemployment rate to start in 2019, about 10%; their unemployment rate had fallen to approximately 8% by the first quarter of 2022. Women aged 16-24 started 2019 with unemployment of just over 5%, and by 2022 their rate had fallen to nearly the same level.

While younger men's unemployment recovery matches the speed of that in the UK as a whole (Murphy 2022), the unemployment of women aged 16-24 had not quite returned to the pre-pandemic level of just over 5%. Older age groups had much more stable rates of unemployment during the pandemic. Those aged 25-49 and women over 50 experienced relatively small changes in unemployment and remained at similar levels in the first quarter of 2022 to three years prior. In contrast, men over 50 have had rising rates of unemployment from 2020Q1 through the first quarter of 2022.

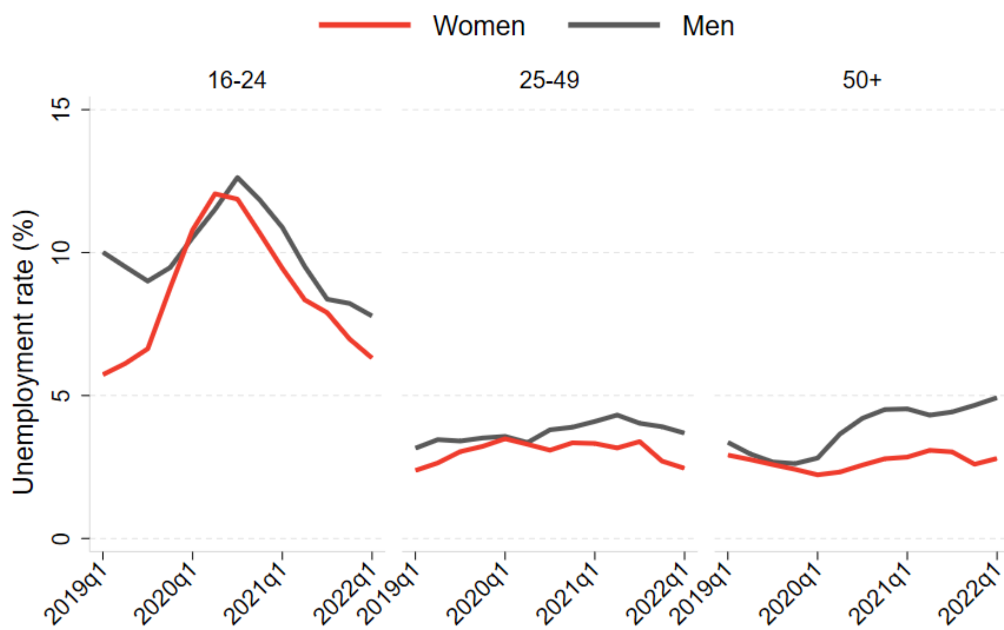

Figure 6: Unemployment by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

Trends in hours and pay 2019-2022

This section presents trends in hours worked and weekly pay in Labour Force Survey data for 2019-2022. Mean hours and pay are adjusted by annual moving averages to avoid seasonal trends. Hours worked and pay per week are summed over all jobs and averaged among all employed people in each group. The figures presented represent all workers, include part-time workers. Nominal wages are deflated to 2019Q1 £ using the quarterly consumer price index including housing costs (CPIH). In general, women tend to work fewer hours and earn less per week on average, explained by their higher participation in part-time work compared to men.

Weekly hours worked

Hours worked per week decreased during the pandemic for all groups and then rebounded to roughly pre-pandemic levels (Figures 7-9). Those with lower levels of qualifications had greater decreases in hours worked (Figure 7), likely because these groups were more likely to work in occupations that were most impacted by lockdown and distancing measures like skilled trades (Figure 8). This pattern holds across age groups (Figure 9), but with a sharper decline in hours worked for older and younger workers during the pandemic.

Figure 7: Weekly hours worked by gender and qualification level
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

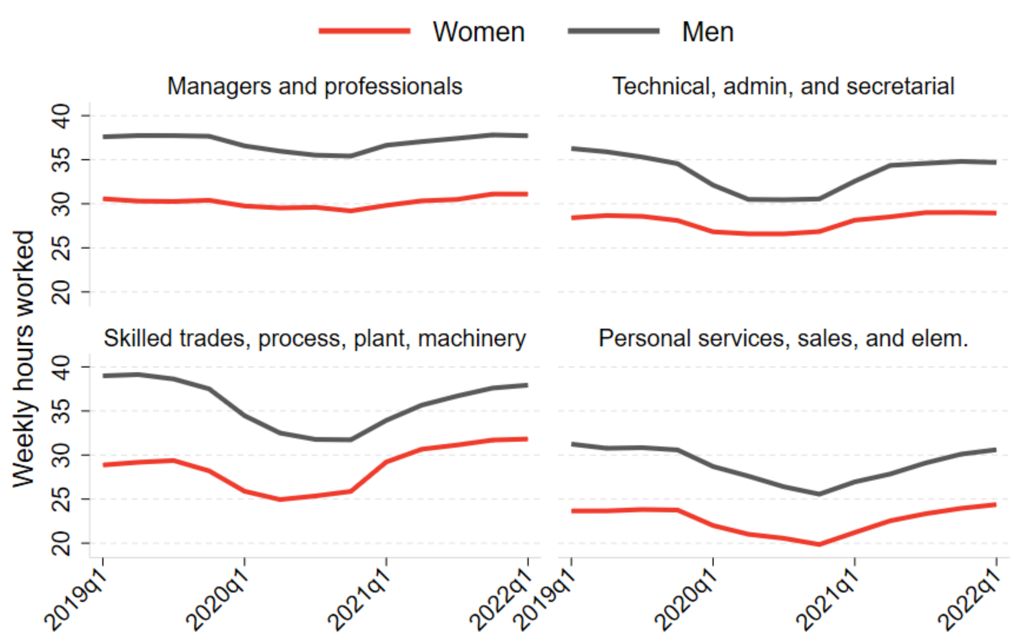

Figure 8: Weekly hours worked by gender and occupation
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

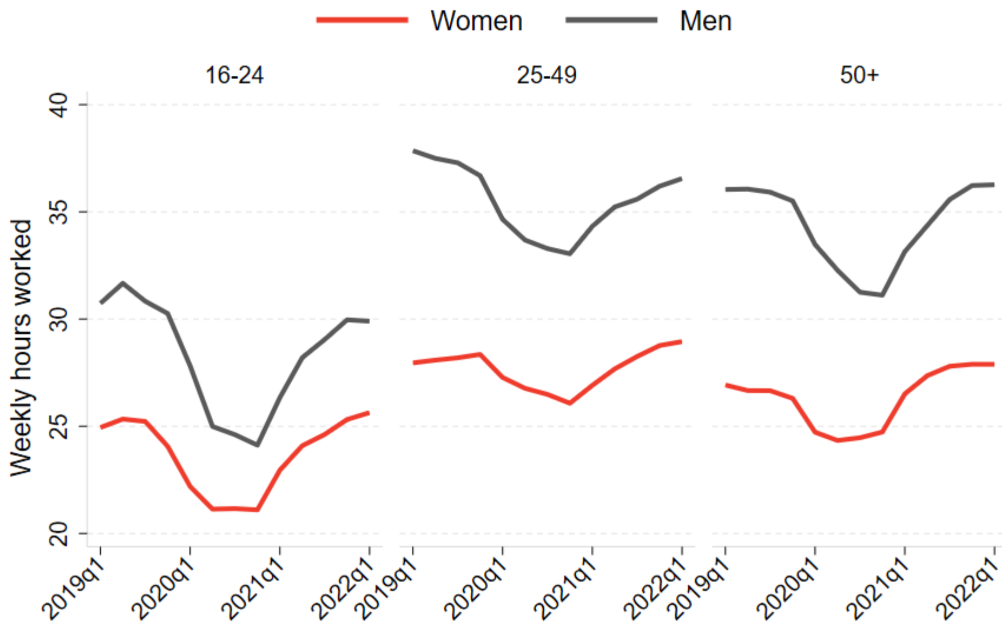

Figure 9: Weekly hours worked by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality.

It is worth noting that across these disaggregations (Figures 7-9), many groups of employed women work slightly more hours per week than they did prior to the pandemic, whereas some groups of men work slightly less. This compounds the differences in employment rates by gender, so that some groups of men (particularly those of working age with fewer qualifications) are less likely to be employed and working fewer hours as compared to 2019.

Total weekly pay

Weekly pay is calculated as a total amount received from all jobs and averaged among all employed people, including those working part-time jobs. Weekly pay is expressed in real 2019Q1 £.

Real weekly pay held fairly steady across gender and qualification groupings from 2019-2022 for those in employment, likely due to furlough schemes (Figure 10). This is in contrast to the UK overall, where reports in 2021 suggested that workers with lower levels of qualifications experienced stronger earnings growth due to a rise in the National Living Wage in 2020 (Cribb et al. 2021). Static pay for those in employment suggests that decreases in household income during the pandemic were more likely to come from disemployment than from reduced hours or pay rates.

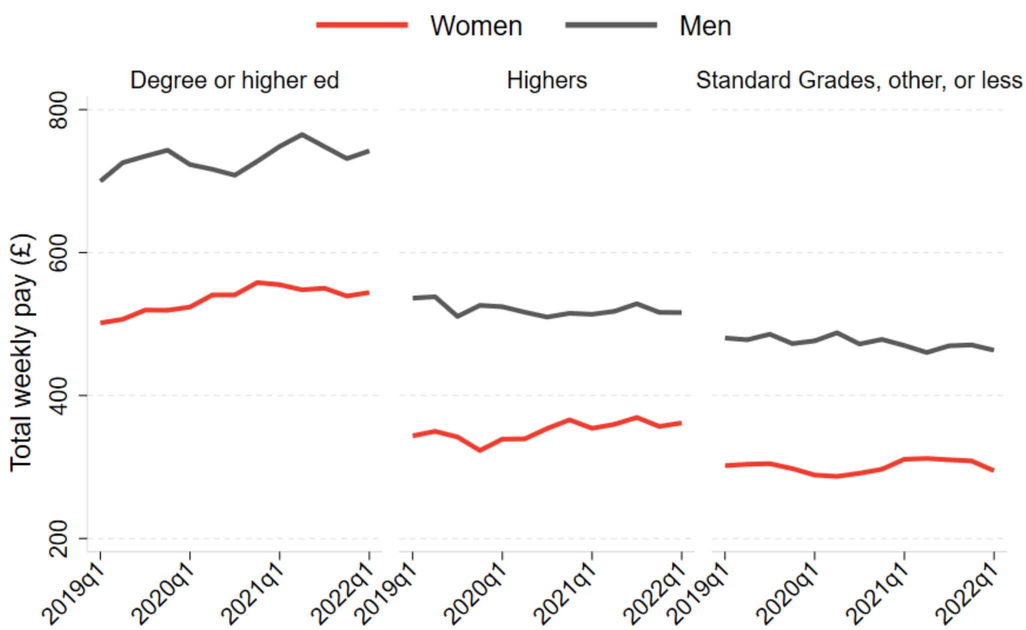

Figure 10: Real weekly pay by gender and level of education
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality. Real weekly pay is expressed in 2019Q1 £.

The differences between these static figures and the rise in real wages over the same period in the Scottish economy overall (Figure 1) are likely due to compositional shifts in the labour market, which have been noted in UK-wide statistics as a key driver of wage growth during the pandemic (Cominetti et al. 2022).[2] Workers with degrees had slight increases in real pay, while those with lower qualifications saw more stagnant pay. Similar patterns held across occupations, with more variation between occupational groupings than over the course of the pandemic (Figure 11).

Trends in weekly pay were slightly more variable within gender and age groupings (Figure 12). Weekly pay trended upwards for women above the age of 50 from 2019-2022; for men, it remained more level until partway through 2020, when it began to climb. Real weekly pay in the last quarter of 2021 and first quarter of 2022 stagnated or fell for most groups due to higher rates of inflation.

[2] Although the LFS is not the preferred dataset for detailed analysis of pay, mean weekly pay for men and women as calculated from LFS data 2019-2022 roughly matches pay as measured in the Annual Survey of Hours and Earnings (ASHE) (Office for National Statistics 2022).

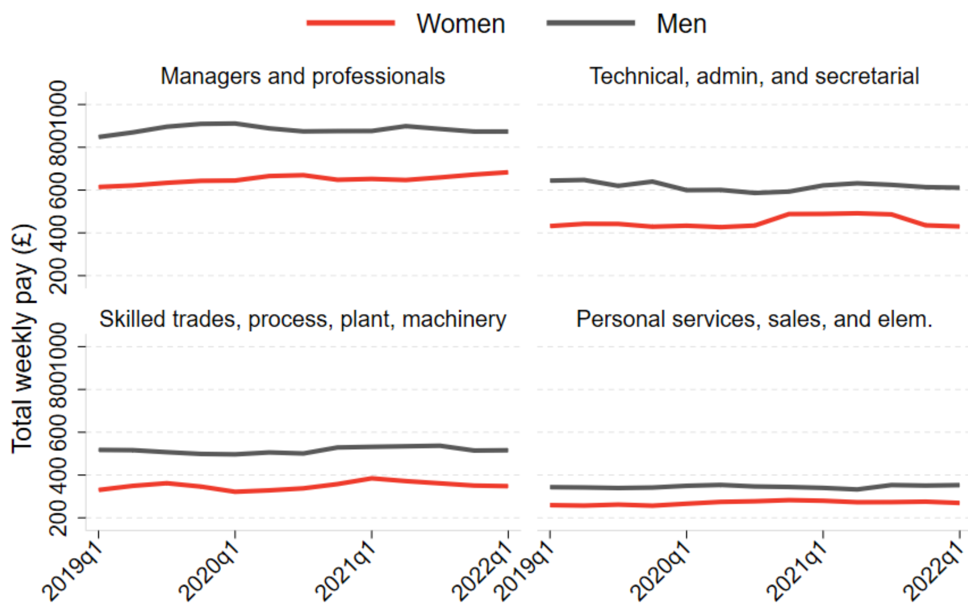

Figure 11: Real weekly pay by gender and occupation
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality. Real weekly pay is expressed in 2019Q1 £.

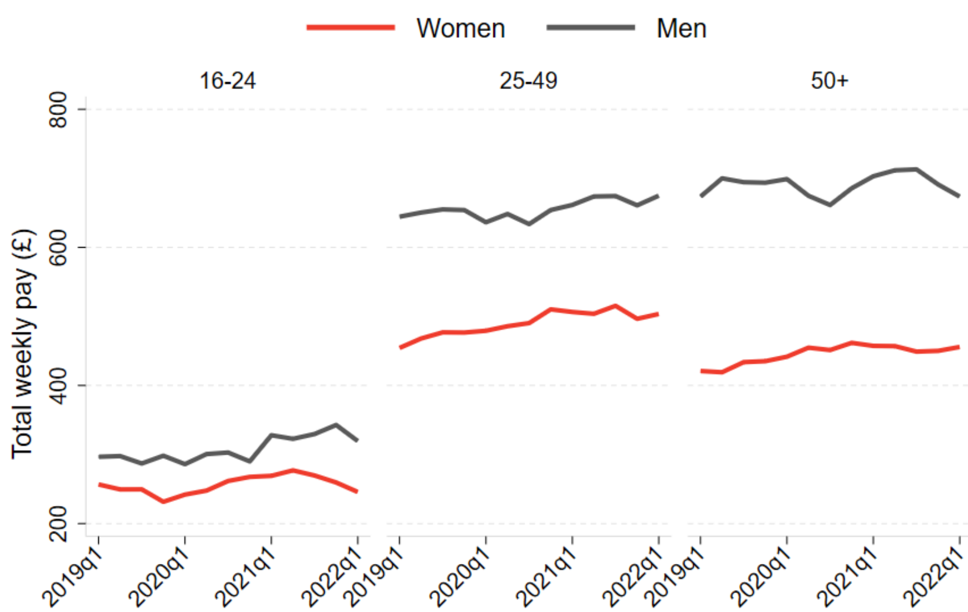

Figure 12: Real weekly pay by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures are smoothed using an annual moving average to account for seasonality. Real weekly pay is expressed in 2019Q1 £.

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Annex: Trends in non-seasonally adjusted population estimates

This annex contains charts of estimated population means and 95% confidence intervals for key employment statistics, disaggregated by combinations of sex, age, and level of qualifications. The means shown in these figures may differ from the main figures because they omit the moving average adjustment for seasonality.

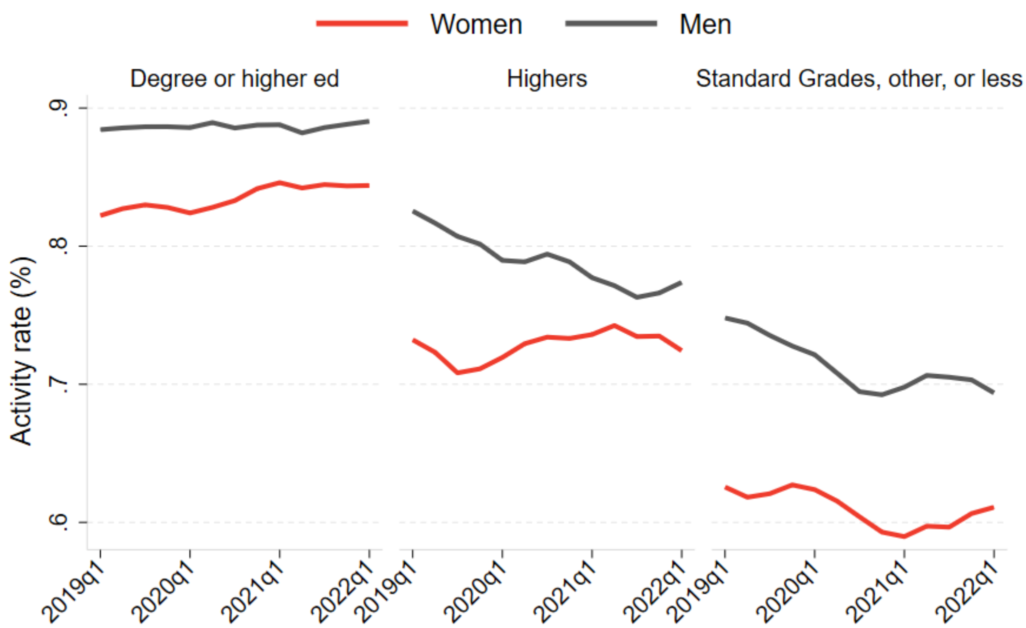

Figure A1: Activity rate by gender and qualification

Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)

Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

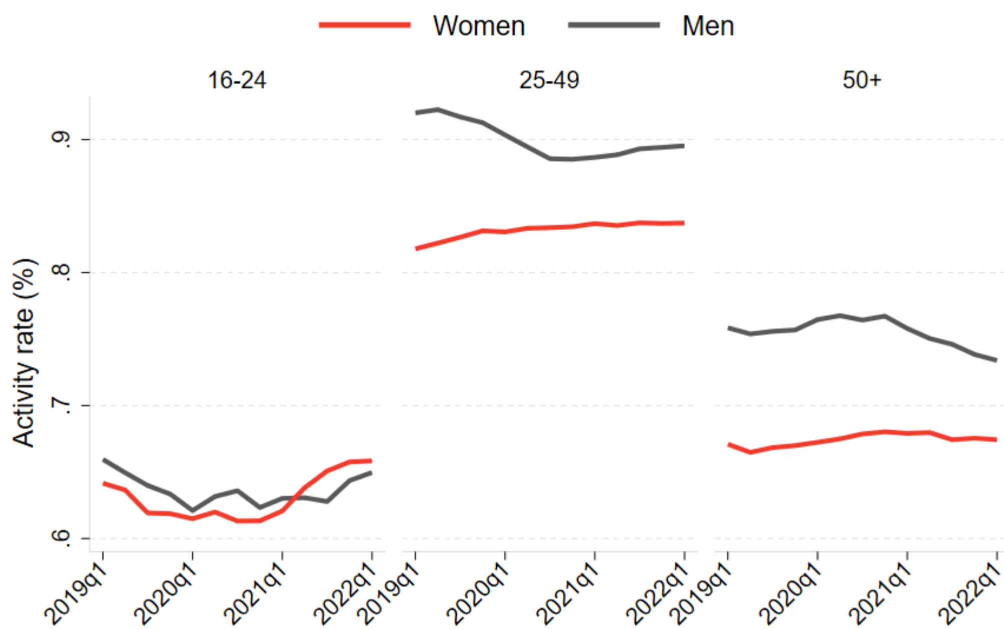

Figure A2: Activity rate by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

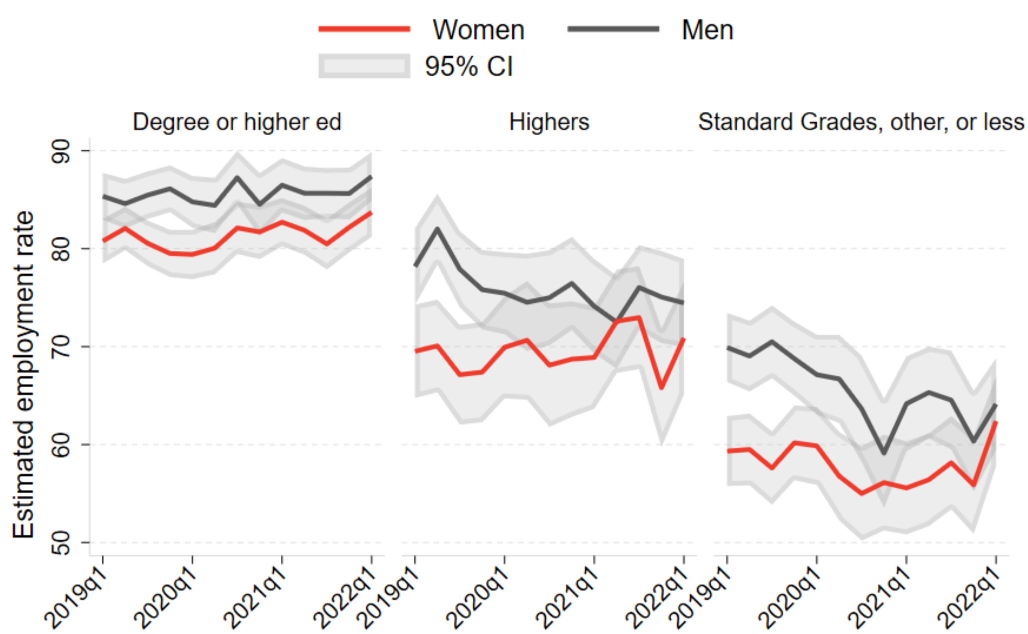

Figure A3: Employment rate by gender and qualification
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

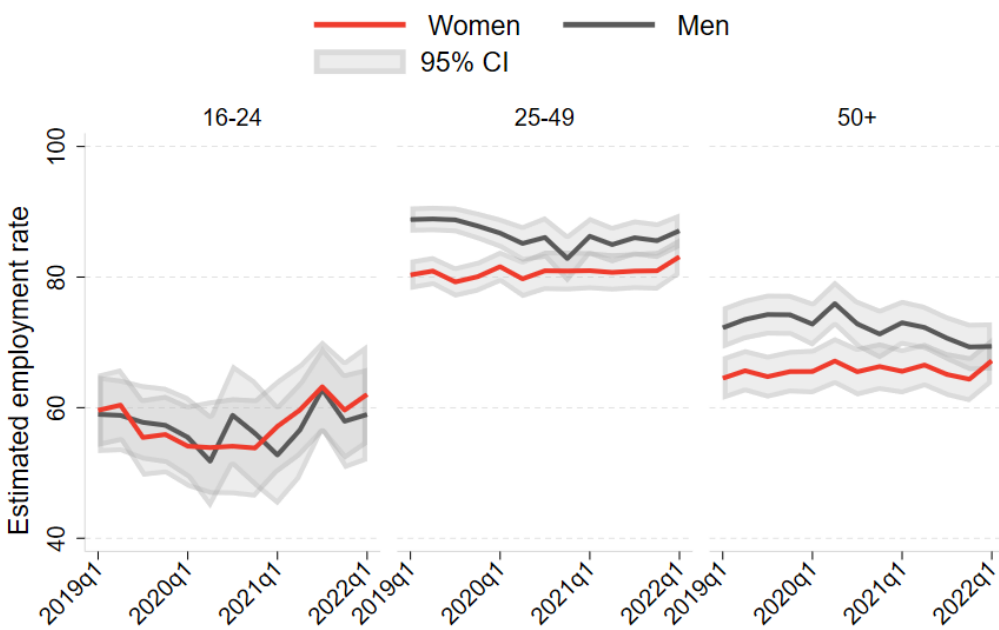

Figure A4: Employment rate by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

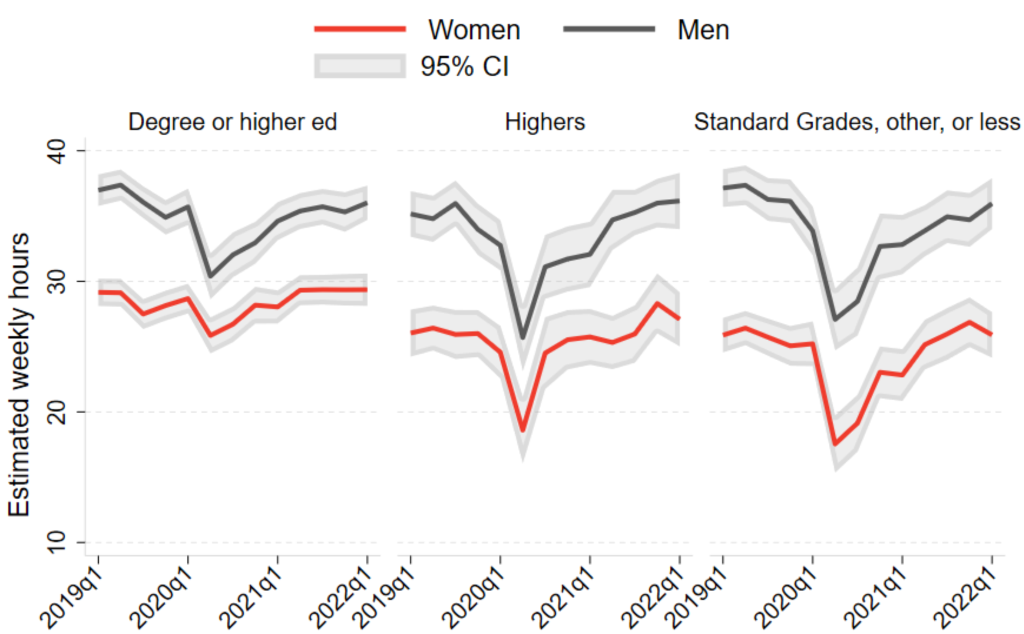

Figure A5: Weekly hours worked by gender and qualification
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

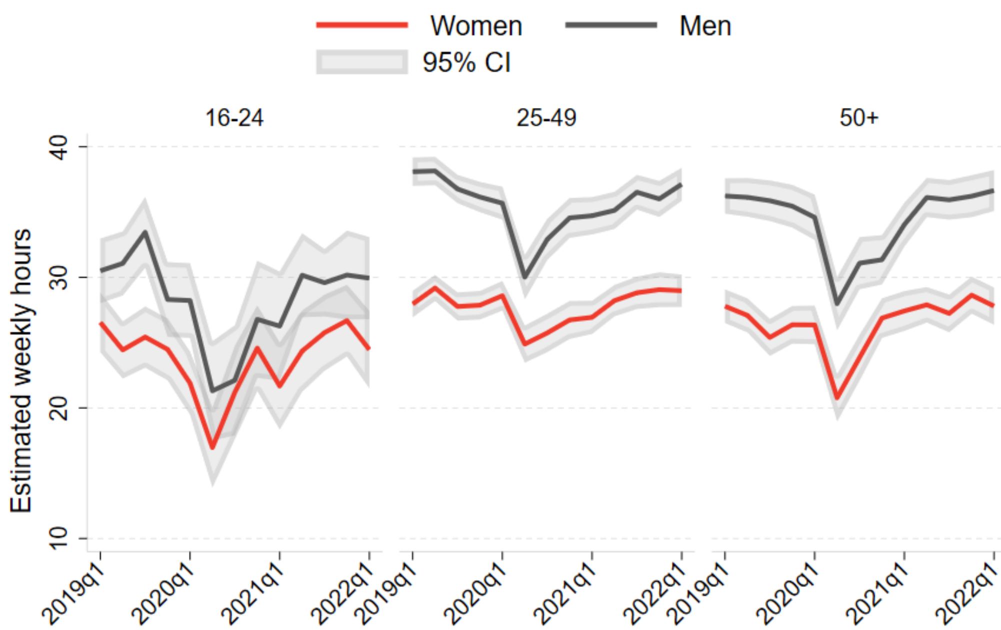

Figure A6: Weekly hours worked by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

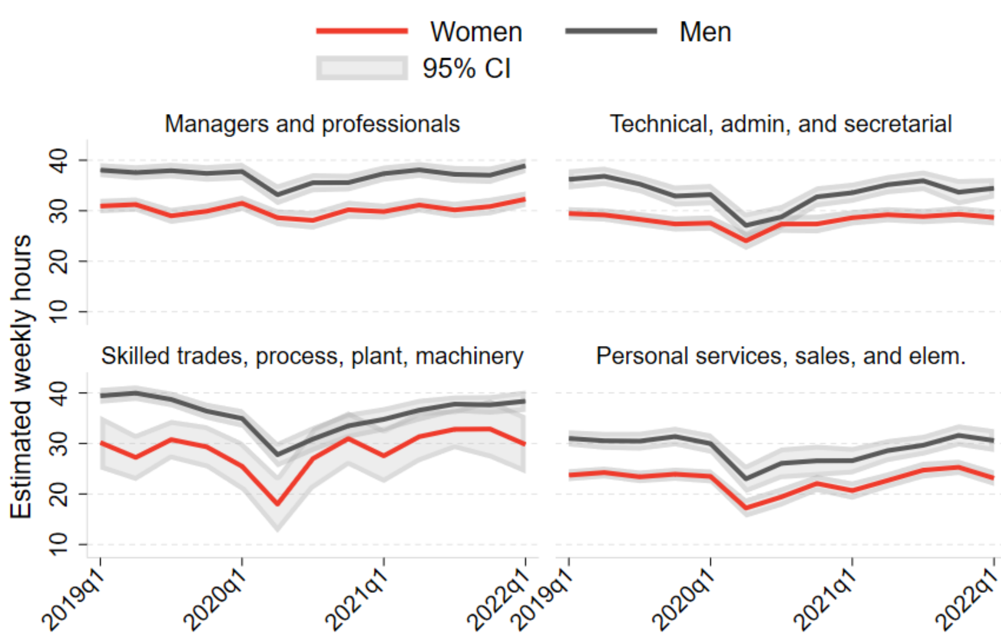

Figure A7: Weekly hours worked by gender and occupation
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals.

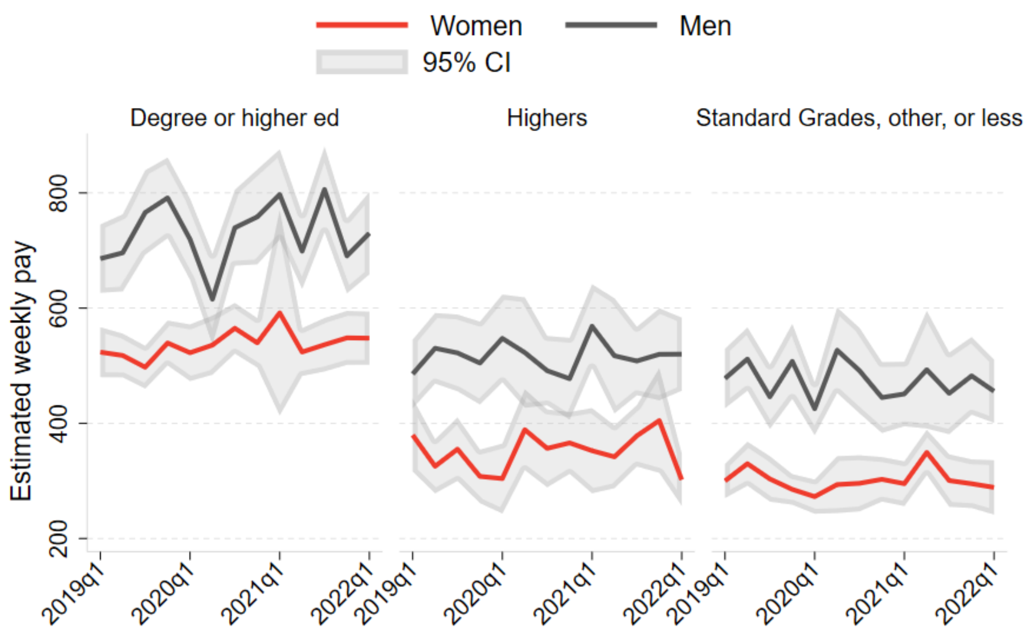

Figure A8: Real weekly pay by gender and qualification
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals. Real weekly pay is expressed in 2019Q1 £.

Figure A9: Real weekly pay by gender and age
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)

Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals. Real weekly pay is expressed in 2019Q1 £.

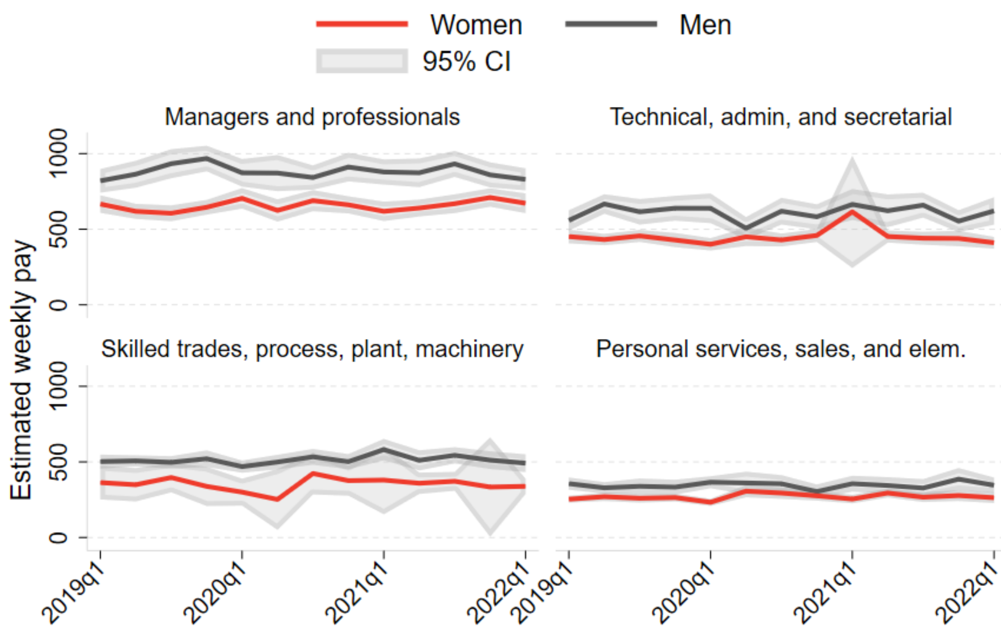

Figure A10: Real weekly pay by gender and occupation
Source: Author calculations from quarterly LFS data, 2010-2022 (ONS 2022)
Notes: All figures reflect non-seasonally adjusted sample means and 95% confidence intervals. Real weekly pay is expressed in 2019Q1 £.

IPPR tax-benefit microsimulation results and policy analysis

Introduction and key findings

This report presents the results of the IPPR tax-benefit microsimulation model for income, inequality, and poverty in the 2022-23 financial year. We discuss the differences in results for two datasets created by modifying Family Resources Survey (FRS) 2019-20 data: one representing employment trends in 2019-20, before the pandemic, and one representing post-pandemic employment. Finally, we use these datasets to analyse the effects of several policies, including the effect of a £25 per week, per child Scottish Child Payment and changes to income and council tax rates.

Key findings

- Incomes overall have risen since just before the Covid-19 pandemic, particularly for households at the lowest end of the income distribution. The increase is driven by higher earned income for most types of households.
- As in our labour market analysis, single working-age males (16-64) are the only group with lower earned income post-pandemic, caused by reduced employment rates.
- Poverty rates have fallen very slightly for most groups, particularly children (by 0.6pp), but the changes disappear when figures are rounded to the nearest percent. The largest decreases by household type are a 1pp decrease in the poverty of single working-age female households, consistent with their increased employment. Single working-age males and mixed pensioner and working-age adult households see a slight rise in poverty.
- Higher earned incomes bring some households out of relative poverty, but these households remain close to the poverty line. Even small changes in tax policy may have noticeable effects on relative poverty rates, particularly if tax rate changes elicit a behavioural response.

Baseline IPPR results

The first dataset is a reweighted version of the FRS 2019-20 data that reflects population estimates for the first quarter of 2022, but leaves employment data unchanged. This dataset is referred to as "original" in tables throughout the report. The second dataset is reweighted to reflect changes both in population and in employment rates for individuals 16-64 between 2019-20 and the first quarter of 2022. This dataset is referred to as "updated" for simplicity.

Comparing results of the IPPR model for these two datasets allows us to estimate differences in income, inequality, and poverty arising from 2022Q1 employment versus what they would have been if pre-pandemic employment rates had persisted. A technical note on the reweighting methodology is included as an appendix to this report.

Changes in taxes, benefits, and household income

First, we consider the overall changes across Scotland in fiscal costings, income, and poverty. Overall tax receipts rise and benefits fall, so that the difference between taxes and benefits is about 9.5 billion after the pandemic vs. a predicted 9 billion if pre-pandemic levels of employment had persisted to early 2022 (Table 1).

Table 1: Difference in predicted costings

Category	Original (£mil)	Updated (£mil)
Taxes - benefits	9,027.94	9,514.82
Total benefits	22,548.46	22,377.48
Total taxes	31,576.41	31,892.29

Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)

These changes in tax receipts and benefits payments are a direct result of changes to income. On average, income rises, resulting in greater tax receipts and a lower total benefits bill. However, increases in income are not equal across the income distribution (Table 2). Those at the lowest end of the income distribution have the largest changes in income, with these increases generally getting smaller as income rises. For example, households in the lowest decile (the lowest-earning 10% of households) have equivalised disposable income that is 4.7% higher based on post-pandemic employment than if employment trends from 2019-20 had persisted, while that of households in the top decile is only about 0.5% higher.

Table 2: Difference in predicted disposable income by decile

Decile	Original (£)	Updated (£)	% change
1	124.43	130.28	4.7
2	305.16	309.08	1.3
3	379.70	381.46	0.5
4	442.95	446.25	0.7
5	506.69	509.51	0.6
6	571.13	574.36	0.6
7	646.38	649.74	0.5
8	740.54	743.65	0.4
9	876.65	879.39	0.3
10	1,432.88	1,439.85	0.5

Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)
Notes: Equivalised disposable income is measured after housing costs.

These differences in income vary between types of households. We define six types of households based on gender and the mix of adults of different ages in each household. These six types and their abbreviations are explained in Table 3.

Table 3: Household type definitions

Household type	Types of adults in household
Pensioner	Only adults over 65
Mixed (WA>50)	At least one adult over 65 and at least one adult 50-65; could also have an adult under 50
Mixed (WA<50)	At least one adult over 65 and at least one adult under 50; no adults 50-65
Single WA female	Only one working-age female (16-65)
Single WA male	Only one working-age male (16-65)
Multiple WA	Multiple working-age adults (16-65); no adults over 65

Figure 1 shows changes in earned and disposable income by household type. Since pensioner-only households do not have any members aged 16-64, their incomes are not weighted differently between the two datasets, and there is no difference in income between the two datasets for this group. Mixed pensioner and working-age adult households see small increases in earned income based on 2022Q1 employment rates, particularly in households with working-age adults under 50. Households with multiple working-age adults have about 1% higher earned and disposable income based on 2022 employment rates. Single working-age adult households have the largest differences in income, with single working-age females earning about 4% more and single working-age males 1.2% less based on employment rates in 2022. These findings are consistent with higher women's employment in 2022 compared to 2019-20 and lower men's employment, particularly among less-educated men.

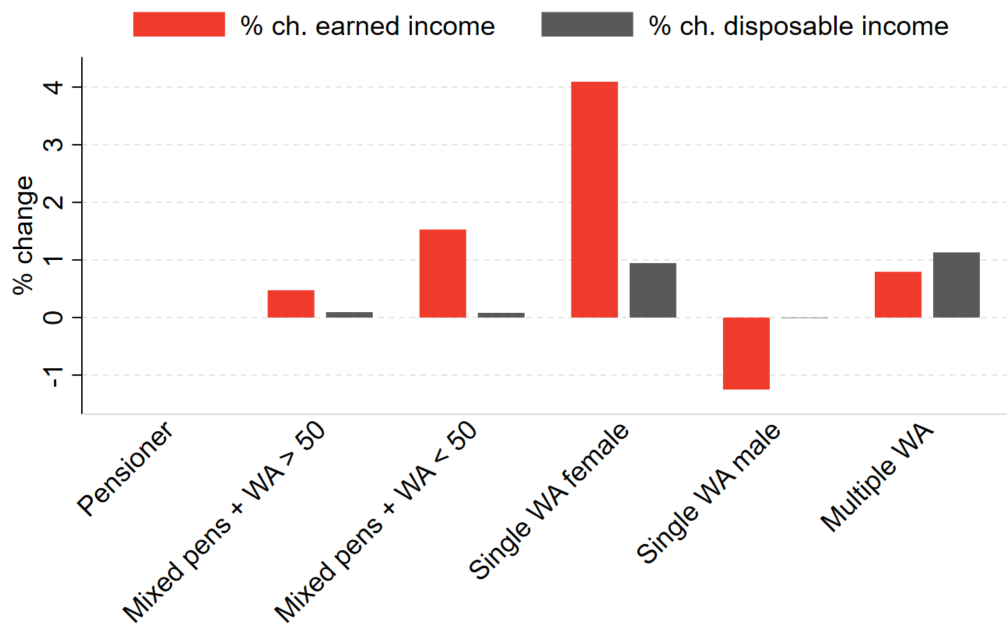

Figure 1: Changes in income by household type
Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)
Notes: Disposable income is measured after housing costs.

Two sources of changes in total and disposable income are changes in taxes paid and benefits received. As with income, pensioners have no change in taxes and benefits (Figure 2). All other groups except single working-age males pay more in taxes and receive less in benefits, consistent with higher income for these households.

Although single working-age males have a relatively large average change in benefits received, this is partially because the average benefits received were relatively low to begin with. In the dataset based on 2019-20 employment rates, single working-age men received £91 in benefits on average, compared to about £96 in the dataset based on 2022 employment rates. This is only about a quarter of the average benefits received by mixed pensioner and younger working-age adult households, the group with the highest average benefits. The average benefits received by single working-age men is just over half of the average benefits paid to single working-age women in both datasets, possibly due to differences in employment patterns and the presence of children in a greater number of single working-age women's households.

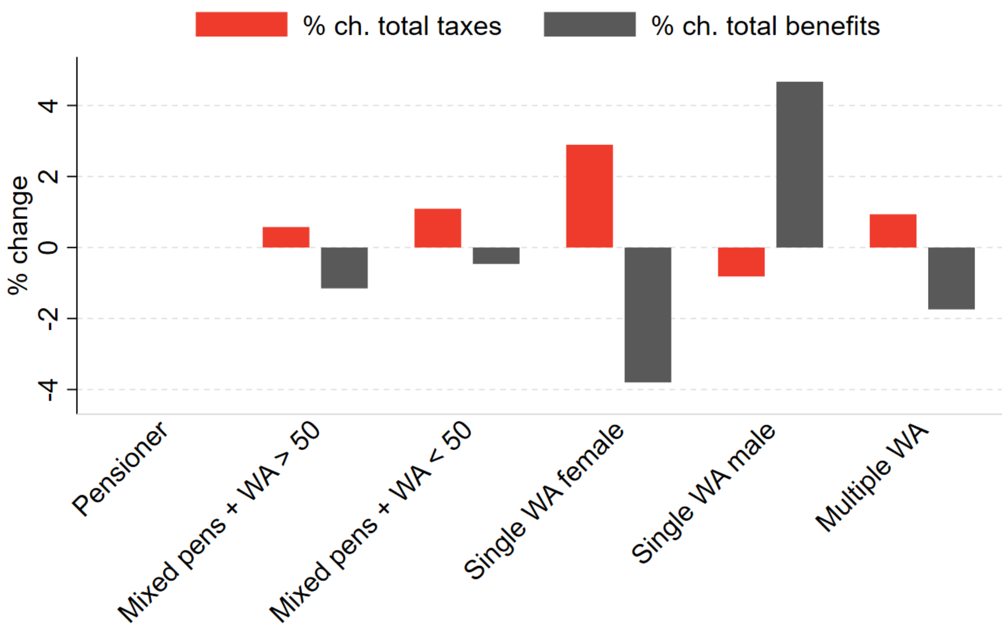

Figure 2: Changes in taxes and benefits by household type
Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)
Notes: The IPPR model calculates benefits takeup by estimating a propensity to receive the benefit among qualifying benefit units.

Changes in inequality and poverty

The IPPR model also gives estimated measures of inequality and poverty. Like income, we look both at overall changes in these measures and at changes by household type.

Overall measures of inequality have mixed differences between the two datasets (Table 4). The 75:25 and 75:50 income ratios rise by 0.01, but the 90:10 and 90:50 ratios both fall by 0.01. Overall inequality as measured by the Gini coefficient falls very slightly from 0.322 to 0.318.

Table 4: Difference in measures of inequality

Measure	Original	Updated
50:10 Ratio	2.02	2.02
50:25 Ratio	1.44	1.43
75:25 Ratio	1.97	1.95
75:50 Ratio	1.36	1.36
90:10 Ratio	3.51	3.53
90:50 Ratio	1.74	1.75
Gini coefficient	0.256	0.252

Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)
Notes: All disposable income percentiles are calculated after housing costs.

There are also minimal differences in relative poverty rates between the two datasets. The poverty line is calculated as 60% of the median disposable income for the entirety of the UK.

The poverty line changes from £315.73 per week based on 2019-20 employment to £314.97 based on 2022 employment. When rounded to the nearest percentage point, the poverty rate does not change between the two datasets for any group, although there are minor decreases across the board consistent with small increases in average incomes (Table 5).

Table 5: Difference in predicted relative poverty rates

Group	Original (%)	Updated (%)
Adults	17.4	17.2
Children	25.4	24.8
Households	19.2	19.0
Pensioners	11.0	11.0
People	18.9	18.6
Working age adults	19.3	19.0

Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)
Notes: Based on a poverty line equivalent to 60% of UK median income as calculated by IPPR model.

Relative poverty rate differences by type of household mirror differences in income (Figure 3). Relative poverty among single working-age women falls by over 1 percentage point (pp) based on 2022 employment as compared to 2019-20 due to their higher rates of employment. Households with multiple working-age adults see a smaller 0.5pp decrease in relative poverty. Contrary to results for income, mixed pensioner and working-age adult households see slightly higher relative poverty rates (by 0.1 to 0.2pp).

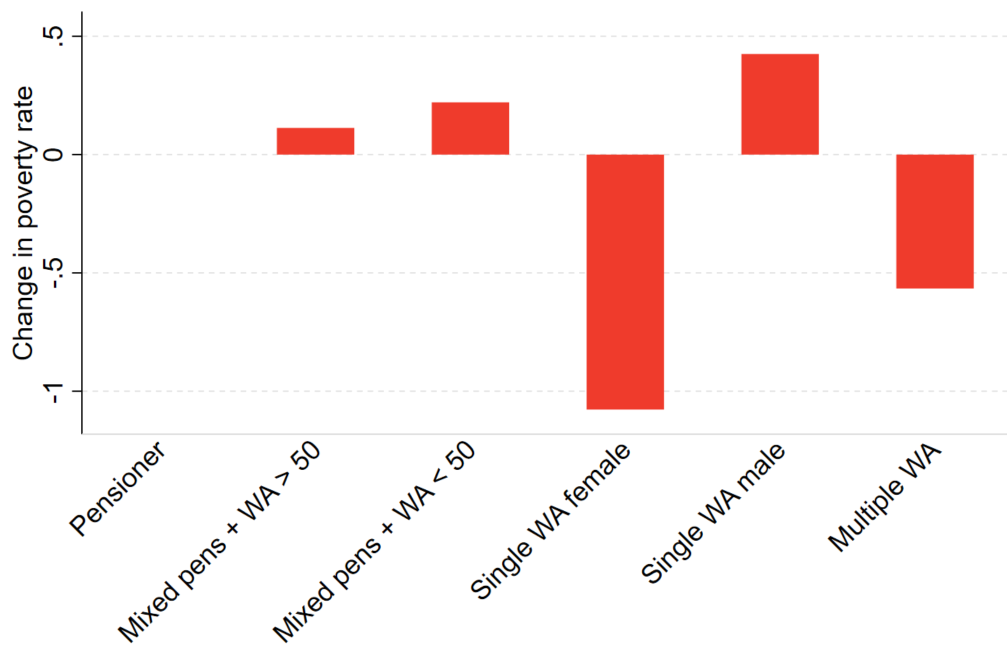

Figure 3: Changes in poverty rate by household type
Source: Author calculations from FRS 2019-20 (DWP 2021) and IPPR model v.02_44 (Kumar 2022)
Notes: Based on a poverty line equivalent to 60% of UK median income as calculated by IPPR model.

The increase in relative poverty for mixed pensioner and working-age adult households despite increases in their average disposable income may be explained by mixed changes among households within these groups. If a few households with much higher income in these groups are weighted more heavily in the version of the FRS based on 2022Q1 employment rates, then average income rises. However, if these households remain out of poverty, but other households in these groups experience lower income and fall into poverty, then the overall relative poverty rate for the group rises as well.

Policy analysis

Throughout the policy analysis, we compare the effects of policies between the two versions of the dataset analysed in the last section: one representing an early 2022 labour market where employment rates are the same by group as they were in 2019-20, and one representing a labour market with employment rates from the first quarter of 2022. The primary comparison is a "difference-in-differences" measure in the sense that we look at how the differences in outcomes caused by a given policy differ between the two datasets.

In normal reporting results of microsimulation, it is standard practice to round percentage point changes to the nearest whole percentage point. For example, a fall of 0.2pp would therefore be normally reported as a 0pp change. In this paper, we have chosen to report the unrounded figures to show where the model states there is a change between the two datasets, on the understanding that the data is experimental and the results will not be used for policy development.

Increase in Scottish Child Payment

First, we model the effects of the Scottish Child Payment (set at £25 per week, per child for all children under 16). The counterfactual is a scenario in which the Scottish Child Payment was never implemented in any form. For consistency with the rest of the analysis in this project, we have modelled these scenarios for 2022, rather than 2023 when full-out of the Scottish Child Payment is expected.

Because households generally have higher incomes in the "updated" dataset reweighted for employment rates in 2022, especially at the lower end of the income distribution, the effects of the Scottish Child Payment (SCP) on income and relative poverty are reduced compared to the "original" dataset reweighted only for population sizes. Differences in the effects of the SCP on inequality are minimal, but there are slightly greater reductions in a few measures of inequality in the updated data.

The difference in relative poverty effects for children is the largest; the reduction in child poverty caused by the SCP is 0.2pp lower in the updated data than in the original data.

Similarly, the proportion of households who gain in income from the SCP is generally higher in the original dataset. The exception is in the second quintile, where proportionally more households gain from the SCP in the updated dataset. This may be due to the labour market adjustments in this dataset, or to a change in the household composition of households that fall into the second quintile.

Changes to income tax

Second, we model changes to income tax rates. We model both a 1pp increase in income tax rates across all bands and a 1pp decrease for all bands. The counterfactual for these changes is the current tax and benefits system.

The 1pp increase in income tax rates for all bands generally increases relative poverty and negligibly reduces inequality. The difference in relative poverty effects is again largest for child poverty, with the tax rate increase raising the child poverty rate by 0.17pp more in the updated dataset than in the original dataset. This is likely due to higher earned income in the updated dataset for some types of households, leading to higher taxes paid and fewer benefits.

However, there are only small differences in the effects of a 1pp decrease in income tax rates on relative poverty rates, with the largest difference in effects being a 0.07 smaller reduction in pensioner poverty in the updated data.

Changes in income are more mixed this time, with some winning and some losing from both the increase and decrease to income tax rates. A 1pp increase in income tax rates creates gains for a few households at the lower end of the income distribution, more so in the updated dataset. These gains arise when some households qualify for more benefits with the new tax rate. The average gain is about £35 per week higher for the lowest income quintile in the updated dataset than in the original.

As expected, more households lose from a rise in income tax rates. Proportions of households losing are greater in the updated data, particularly for the first quintile, although the average losses are negligibly different between datasets. The difference in the proportion of households losing due to the tax increase may be due to higher employment rates, and thus more taxable income.

Similar patterns hold for the 1pp decrease in income tax rates, with gains and losses reversed. The proportion of households that gain from the tax rate change increases with quintile. More households gain at each quintile in the updated data than do in the original data, especially for the first quintile, where the proportion of gainer households is 0.9 higher. Average gains in income are small and minimally different between datasets.

Only a few households lose from the decrease in income tax rates, with the only difference between datasets being a lower proportion (by 0.08%) of households in the first income quintile that lose from the policy in the updated data. This is likely due to a reduction in the benefits that these households qualify for. The average loss in the first income quintile is reduced by £64 per week in the updated data.

Changes to council tax

Third, we model a 2% increase and a 2% decrease in the council tax rate. As with the income tax policy analysis, the counterfactual is the current tax and benefits system.

Due to the small changes in the council tax amounts, its regressive nature, and the existence of Council Tax Reduction which largely offsets changes in tax for the lowest income households, relative poverty and inequality do not change appreciably in either version of the dataset.

The 2% increase in council tax rates creates fewer "gainers" and more "losers" in the updated data than in the original data. The differences are larger at the lower end of the income distribution; that is, the increase in tax hurts those with lower incomes more in the updated data. There are no noticeable differences in the changes in gains and losses between datasets.

The effects of the 2% decrease in council tax rates on the proportion of those who gain and lose from the policy differ between datasets across the income distribution. More gainers are created at higher quintiles in the updated data, but fewer at the first and second quintiles. Similarly, slightly more households at the first and second quintiles lose from the decrease in council tax than at higher quintiles, particularly the third quintile. As with the 2% decrease, the amount of gains and losses do not change noticeably between datasets.

Implications for policy

Our analysis highlights a few issues that policymakers should be aware of.

First, when earned incomes rise, the effects of the Scottish Child Payment on child poverty (and relative poverty in general) fall. This is because more households are already out of relative poverty, not because the policy is less effective.

Second, when proportionally more households have earned income, particularly at the lower end of the income distribution, changes in income tax are more likely to have progressive effects.

Third, however, a rise in earned income brings some households out of relative poverty, but these households likely remain close to the poverty line. Even small increases in income tax rates may have a larger effect on relative poverty than when employment rates and earned income are lower, particularly if higher taxes induce a behavioural response that reduces labour supply.

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Technical note on FRS 2019-20 reweighting methodology

Context

This technical note provides a description of the methodology used to reweight the Family Resources Survey (FRS) 2019-20 data to obtain an “updated” version of the FRS reflecting the population in 2021-22.[1] All analysis was performed in Stata (StataCorp 2021). Code used to implement the following reweighting methodology is available upon request.

Survey data typically includes unit-level weights (also called grossing factors), which reflect the number of units in the population represented by each unit in the survey sample. For instance, a weight of 100 for a person-level observation in the FRS indicates that that observation represents 100 people in the UK population.

To create an updated version of the FRS for 2021-22, we reweight the 2019-20 FRS to reflect labour market characteristics calculated from the first quarter of Labour Force Survey (LFS) data for 2022 (NISRA, Central Survey Unit, ONS, Social Survey Division, 2022). Despite the availability of 2020-21 FRS data, we choose the 2019-20 data because the limited sample size and possible measurement issues induced by the Covid-19 pandemic make the 2020-21 data less reliable. The goal of the reweighting is to make the weighted 2019-20 data look more similar to the (as yet unknown) 2021-22 population estimates, including labour market characteristics like employment rates among different groups of people. The reweighted data is then used as an input into IPPR tax modelling software to obtain a snapshot of income, income distribution, and poverty in financial year 2022-23.

Reweighting groups

We match labour market characteristics within groups to improve the accuracy of the reweighting. Groups are defined for all adults 16-64 based on combinations of sex, age, and level of highest qualification. Sex and age both have two categories, and level of qualifications three, so that all observations are sorted into one of 12 total groups.[2] Categories of each

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[1] The 2019-20 FRS data is publicly available through the UK Data Service website (Department for Work and Pensions, Office for National Statistics, NatCen Social Research 2021).

[2] To match 2022 population estimates, two additional groups are included in the reweighting (men and women aged 65+). The reweighting for these groups ensures that the adult weights sum to the estimated population of each group of adults in 2022, rather than matching an employment rate within those groups.

characteristic defining the groups are shown in Table A1. For example, one group contains all women aged 50-64 with a degree or a higher education qualification.

Although the target population is Scotland, the IPPR model uses the FRS sample for all of the UK to calculate tax implications and the poverty line. Therefore, the reweighting is conducted separately for Scotland and rUK within the groups defined in Table A1.

Table A1: Group classifications for reweighting

Sex	Age	Qualification	Group
Women	50+	Degree or higher ed	A
		Highers	B
		Standard grades	C
	16-49	Degree or higher ed	D
		Highers	E
		Standard grades	F
Men	50+	Degree or higher ed	G
		Highers	H
		Standard grades	I
	16-49	Degree or higher ed	J
		Highers	K
		Standard grades	L

Calculation of target population sizes and employment rates

We produce two reweighted versions of the FRS 2019-20 data. The first updates the weights assigned to individuals in the FRS to match estimated population sizes from the first quarter of 2022. This updating is done to reflect any changes in the populations of each group post-pandemic, and acts as a baseline dataset for the IPPR model. The population estimates come from quarterly LFS data for the first quarter of 2022. The second reweighted dataset is updated to reflect both population size changes and changes in the employment rate within each group, and acts as the comparison dataset for the IPPR model. As with the first reweighted dataset, the population estimates come from LFS data, as do employment rate estimates for each group.

The LFS is designed to capture up-to-date information on the labour market at the individual level, while the FRS is recommended as a primary source of household income information (Office for National Statistics 2022). There are significant differences between employment rates obtained from the FRS and those calculated from LFS data. Therefore, instead of matching the absolute employment rate in the 2022Q1 LFS, we calculate the change in the employment rate for each group between the 2020Q1 and 2022Q1 LFS estimates and apply that same percentage point change to the employment rate for each group in the 2019-20 FRS. The resulting employment rate is the target rate for the reweighting, which represents the 2021-22 FRS.

Reweighting of FRS data

For the first reweighted dataset, target population sizes for each group are obtained from LFS 2022Q1 population estimates. We then use the Stata command sreweight to generate new individual-level weights for the FRS 2019-20 data that match the target size for each group (Pacifico 2014). Adult weights are then averaged within each household and applied to all household members.

Producing the second reweighted dataset requires a distinction between target employed and unemployed populations within each group. For each group, we multiply the target employment rate by the population size (obtained from LFS 2022Q1 population estimates) to obtain target employed and unemployed population sizes. The same reweighting procedure described above is applied to the FRS sample, this time to match both population and employment rate changes between 2019-20 and 2022. Groups for men and women in Scotland and rUK are reweighted for population sizes, but not for employment rates.

The IPPR model also calls on data from the Households Below Average Income 2019-20 data (Department for Work and Pensions 2022), which uses most of the FRS household sample but omits some households. These data are used to produce measures of inequality and poverty. The process described above to obtain two reweighted datasets, one adjusting for population changes between 2019-20 and 2022 and the other adjusting for both population and employment changes, is applied to HBAI 2019-20 data as well. These form another input into the IPPR model to obtain estimates of income, poverty, and inequality in 2022-23.[3]

Verification of reweighting process

We verify that the reweighting has been successful using several checks. First, we check that the sum of the individual weights by group match the targets for both reweighted datasets.

Second, we compare each group's weekly hours worked and weekly pay in the reweighted FRS to the 2022Q1 LFS data to make sure that these characteristics are comparable. Because FRS and LFS generally yield different estimates, we test that the differences in mean hours and pay between the reweighted FRS (representing 2021-22) and 2022Q1 LFS are not significantly different than the differences in means between the original 2019-20 FRS and 2020Q1 LFS. Confidence intervals for these differences between versions of the FRS and LFS are shown in Figures 1-2. Groups are indexed in Table A1 for reference.

Since the purpose of this project is to study the impact of the pandemic on income, poverty, and inequality, the most important measure to match is weekly pay. Based on Figure A1, the differences between the reweighted FRS and the LFS 2022Q1 estimates are close to the same differences for the original FRS and the LFS 2020Q1, although for all but a few groups we

[3] HBAI data captures the same sample as FRS, excluding only households containing absent partners. HBAI also uses the HMRC Survey of Personal Incomes (SPI) to adjust very high incomes. As a result, the weights in HBAI data are slightly different to those in FRS data, and are reweighted separately in our analysis.

cannot conclude that the reweighted FRS is strictly within the usual margin of difference from the LFS 2022 data. The mean difference in the difference of means between surveys is about £8.46, with a maximum difference in differences of £77.81 per week (measured in 2019Q1 £) for women over 50 with Standard Grade qualifications.[4]

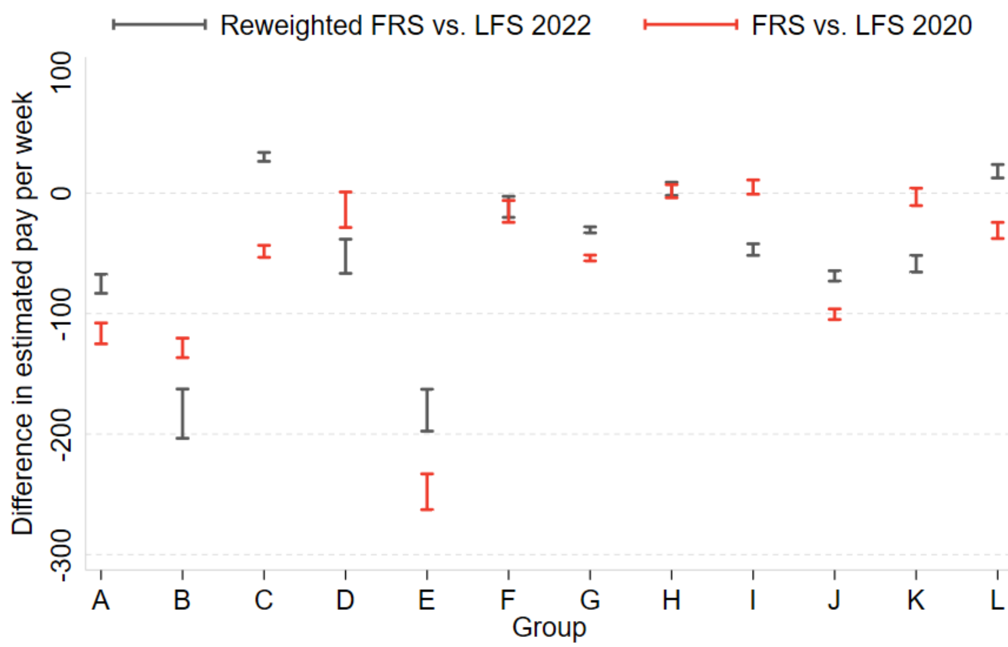

Figure A1: Differences between FRS and LFS measures of weekly pay
Source: Author calculations from quarterly LFS data 2019-2022 (ONS 2022), and annual FRS data 2019-20 (Department for Work and Pensions, Office for National Statistics, NatCen Social Research 2021)
Notes: Each range shows the 95% confidence interval for the difference between weekly pay for each group as measured in the FRS and the first quarter of LFS data for the given year. Differences are calculated as the mean value in the FRS less the mean value in the LFS. For comparison purposes, all pay is expressed in 2019Q1 £, although pay measures are expressed in nominal terms for input into the IPPR model.

Similarly, differences in weekly hours worked are generally close in the reweighted data to those in the actual data, but significantly different in statistical terms (Figure A2). For instance, the largest difference between the reweighted and original data is for women 50+ with Higher level qualifications or equivalent. For this group, the reweighted FRS underestimates hours worked by about an hour per week compared to the LFS 2022Q1 data, whereas the FRS 2019-20 data overestimated hours worked by over five hours. The mean difference in the differences between surveys is about two hours of work per week across groups. As hours of work is not in and of

[4] Interestingly, the poorest "fit" in terms of matching the usual difference in pay and hours between the FRS and the LFS survey data tends to be for women over 50 (see groups A, B, and C in Figures 1-2). This is possibly an indication that the labour market behaviour of this group changed during the pandemic in ways that are not well-reflected by this method of updating the FRS data. Further research on incomes and the labour market following the Covid-19 pandemic should pay particular attention to women over 50 and how their behaviour has changed since before the pandemic.

itself a determinant of benefits or other income, mismatch between the reweighted data and the unknown actual values are not expected to substantially affect the results from the IPPR model.

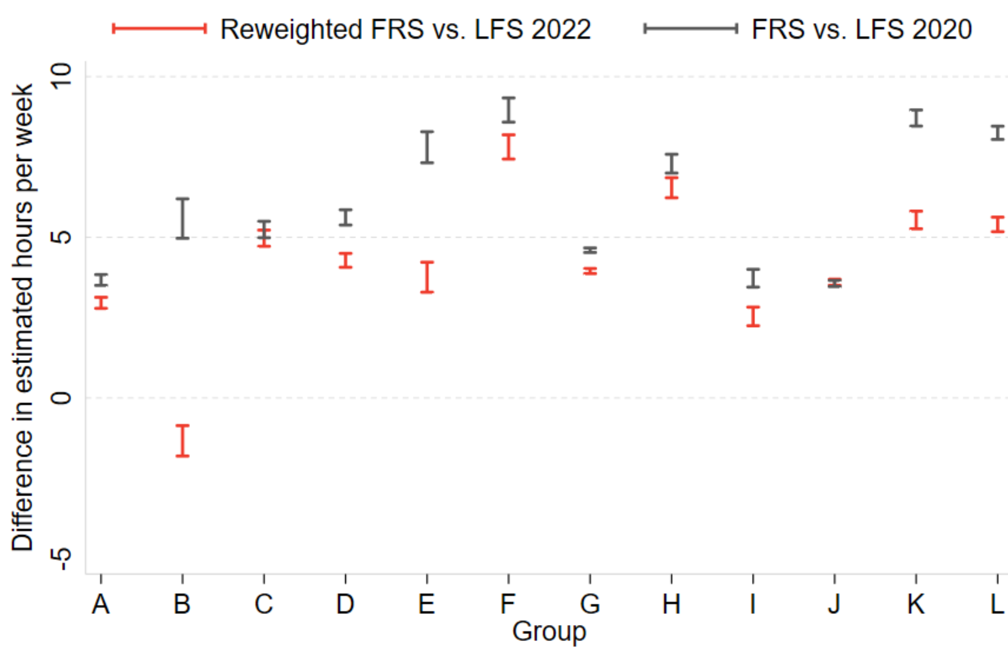

Figure A2: Differences between FRS and LFS measures of weekly hours worked
Source: Author calculations from quarterly LFS data 2019-2022 (ONS 2022), and annual FRS data 2019-20 (Department for Work and Pensions, Office for National Statistics, NatCen Social Research 2021)
Notes: Each range shows the 95% confidence interval for the difference between weekly hours worked for each group as measured in the FRS and the first quarter of LFS data for the given year. Differences are calculated as the mean value in the FRS less the mean value in the LFS.

Transitioning from individual-level analysis of the labour market to household-level analysis of income introduces two issues. Both arise because household weights are an average of all adults in the household, and households are often comprised of adults who were in different groups in the reweighting process. The first is that household weights may not change much if reweighting at the individual level "cancels out" when averaged. The second (and more impactful) issue is that, if household type is systematically related to the groups used for reweighting, then reweighting may change how well the data reflect the actual shares of different household types in the population.

Our third check on the accuracy of the reweighting process is to look at how the proportions of different types of households change between versions of the reweighted dataset. Table A2 shows the distribution of household types in three versions of the FRS 2019-20 data (for Scotland only): the original dataset, the dataset reweighted for population sizes in 2022Q1, and the dataset reweighted for population sizes and employment rate changes in 2022Q1.

Table A2: Distribution of household types in Scotland

Household type	% of original FRS households	% of FRS households, reweighted for population 2022Q1	% of FRS households, reweighted for population and employment 2022Q1	# sample households
Pensioner only	24.99	25.03	25.00	864
Mixed pensioner and working-age adult (50+)	4.13	4.11	4.09	127
Mixed pensioner and working-age adult (16-50)	1.39	1.48	1.44	32
Single working-age female	13.30	13.64	13.59	422
Single working-age male	10.18	10.29	10.43	254
Multiple working-age adults	46.01	45.45	45.46	1022

Source: Author calculations using FRS 2019-20 data (ONS 2022)

We conduct t-tests of the difference in population proportions between the two reweighted versions of the FRS dataset (the third and fourth columns of Table A2). No differences are significant at the 95% level of confidence. Nevertheless, small differences in proportions of household types represented in the data may still contribute to the baseline differences between the two datasets.

An alternative approach to data updating

Reweighting observations in the FRS dataset to reflect 2022Q1 population sizes and changes in employment rates is one approach to "updating" the data. Another approach to matching employment and wage data in the first quarter of 2022 would be to reassign employment randomly within groups, possibly with some further adjustments to match average wage rates within groups.

Random reassignment of employment status by group would explicitly match a target employment rate, just like the reweighting process. However, it would randomly choose people within each group to either move into or move out of employment to match the target rate. In a simple implementation, this process is completely random, and does not make the assignment based on who in each group was most likely to move in or out of employment through the pandemic period. A more complicated version of this random assignment would be to estimate a propensity to be in work in 2022Q1 contingent on group and other individual and/or household characteristics, and move individual observations in or out of work based on that propensity. This process would introduce another estimation step (and additional uncertainty) into the updating process. Reweighting partially sidesteps these issues, although it is also agnostic to other characteristics beyond group when up- or down-weighting given individuals.

Regardless of how the random process is informed, there is still the issue of assigning a pay rate to those who are moved into work. The group average could be assigned, but as with a completely random reassignment process, that decision ignores other personal characteristics that determine pay. A more complex assignment of a pay rate could estimate pay contingent on group and additional individual or household characteristics, but again, this process would introduce more uncertainty. Further adjustments could be made to match average pay rates within groups, including multiplying each individual's pay by the same factor or using data from the LFS in 2022Q1 to estimate who is most likely within each group to have higher or lower wages than the group average. Reweighting avoids these issues by preserving the wage information of employed individuals and up- or down-weighting people within each group as needed to meet the target group average employment rate.

A further challenge of the employment reassignment and pay adjustment approach is mirroring changes in population by group between 2019-20 and 2022Q1. Beyond creating entirely new or duplicate observations, the only way to make these adjustments is by reweighting. Updating the baseline FRS to match 2022Q1 population sizes would therefore require reweighting regardless of the approach used to match employment data. If the population adjustment is not done, then any differences in the updated data compared to the original FRS 2019-20 would not take into account how the population structure changed during the pandemic. Since reweighting can be easily adjusted to accommodate matching both population changes and target employment rates, that approach is preferred over direct reassignment and adjustment of key variables.

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