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Active labour market programmes for young people in high-income countries: a component network meta-analysis

Technical report



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David Taylor, Katherine Young, Emily Tanner-Smith, and Aron Shlonsky declare that they have no financial, professional, or personal conflicts of interest related to any of the primary studies included in this analysis. None was involved in the design, delivery, evaluation, or funding of any included intervention.

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Executive summary

This review synthesises existing evidence evaluating active labour market programmes (ALMPs) for young people in high income countries. Using a multivariate hierarchical Bayesian component network meta-analysis (CNMA), the impact of 15 individual components delivered as part of the evaluated programmes are assessed across seven categories of employment, education and labour market participation outcomes.

The components of ALMPs that are assessed for effectiveness are: basic, soft and behavioural skills training, off- and on-the-job, job specific technical skills training; self-employment support; employment support covering job search preparation, job search assistance, employment counselling, employment coaching, and financial assistance; and employment experience covering paid and unpaid temporary work experience; and subsidised employment encompassing wage subsidies and public works. The structure and definitions of these components build on those underpinning the Puerto et al (2022) systematic review of the Impact of Active Labour Market Programmes on Youth Employment.

This review was commissioned by the Youth Futures Foundation to inform an extension to its Youth Employment Toolkit. The Toolkit presents a synthesis of the impact, cost, and evidence quality of interventions designed to improve labour market outcomes for young people in high-income countries. The findings presented in this report substantially extend the range of measures and outcomes that could be used to inform the Toolkit. Key findings are described below.

Skills development interventions

Impact of Basic Skills Training

Basic skills training focuses on enhancing foundational competencies such as literacy, numeracy, and digital skills that are essential for individuals to effectively engage in education, training, or employment.

Employment and labour market: Basic Skills Training has low level impact overall on labour market outcomes. It has a 65% probability of having an impact on recent employment but much lower likelihood of impact on currently employed (31%) and currently Not in Employment, Education or Training (NEET). There is little evidence to suggest basic skills training affects employment compensation or duration although there is some chance it can increase hours worked.

Education and skills: Basic Skills Training has high probability (75%) of a positive effect on apprenticeship participation. It has medium probability (62%) of having a positive impact on attainment of occupational licence but very low probability (8%) of positive impact on secondary school completion.

Table 1 Summary of findings for Basic Skills Training

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.02 [-0.10, 0.14]	●	30.8%
Recent Employment	0.11 [-0.19, 0.40]	⊕⊕	64.5%
Currently Unemployed	0.33 [0.06, 0.60]	⊖⊖⊖	0.3%
Currently NEET	0.14 [-0.21, 0.49]	⊖⊖	13.8%
Employment Compensation			
Labour Earnings	-0.09 [-0.25, 0.06]	⊖	3.4%
Wages	-0.14 [-0.58, 0.32]	⊖⊖	21.2%
Employment Duration			
Period Employed	0.04 [-0.10, 0.18]	●	43.3%
Hours Worked			
Hours Worked	0.07 [-0.21, 0.36]	⊕	54.7%
Education and Skills			
Apprenticeship participation	0.22 [-0.29, 0.74]	⊕⊕⊕	74.6%
Occupational licence obtained	0.12 [-0.32, 0.55]	⊕⊕	62.2%
Secondary School (ISCED 3) Completion	-0.05 [-0.19, 0.09]	⊖	8.1%
Secondary School (ISCED 3) Participation	-0.09 [-0.59, 0.42]	⊖	29.8%
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.15 [-0.31, 0.60]	⊕⊕	67%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.04 [-0.42, 0.48]	●	47.2%
Short-Cycle Tertiary (ISCED 5) Completion	-0.06 [-0.52, 0.41]	⊖	32.6%
Short-Cycle Tertiary (ISCED 5) Participation	-0.01 [-0.54. 0.51]	●	41.3%
Bachelor's Degree (ISCED 6) Completion	0.14 [-0.35, 0.62]	⊕⊕	64.5%
Bachelor's Degree (ISCED 6) Participation	0.02 [-0.24, 0.27]	●	40.5%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ⚪ Little or no effect, ➕ Low positive impact, ➖ Low negative impact, ➕➕ Medium positive impact, ➖➖ Medium negative impact, ➕➕➕ High positive impact, ➖➖➖ High negative impact.

Impact of Soft Skills Training

Soft skills training concentrates on developing essential skills such as communication, teamwork, problem-solving, decision-making, critical thinking, and analysis.

Employment and labour market: Soft Skills Training is unlikely to have a positive impact on labour force status. However, it is likely to have a high probability of a positive impact on wage levels (86%) but not earnings. It is unlikely to increase time spent in employment or hours worked.

Education and skills: Soft Skills Training can meaningfully increase apprenticeship participation (75% likelihood) and occupational licence attainment (63%). It may have some limited effect on completion of secondary school.

Table 2 Summary of findings for Soft Skills Training

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.03 [-0.14, 0.20]	⚪	39.4%
Recent Employment	0.01 [-0.19, 0.21]	⚪	33.5%
Currently Unemployed	0.02 [-0.41, 0.44]	⚪	37.7%
Currently NEET	0.06 [-0.43, 0.54]	➖	33.4%
Employment Compensation			
Labour Earnings	0.02 [-0.14, 0.18]	⚪	34.7%
Wages	0.30 [-0.16, 0.76]	➕➕➕	86.1%
Employment Duration			
Period Employed	-0.08 [-0.46, 0.32]	➖	27%
Hours Worked			
Hours Worked	-0.02 [-0.22, 0.19]	⚪	26.4%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Education and Skills			
Apprenticeship participation	0.22 [-0.27, 0.74]	⊕⊕⊕	75%
Occupational licence obtained	0.11 [-0.28, 0.50]	⊕⊕	62.5%
Secondary School (ISCED 3) Completion	0.05 [-0.12, 0.22]	⊕	50.5%
Secondary School (ISCED 3) Participation	0.05 [-0.46, 0.56]	⊕	50.9%
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.10 [-0.35, 0.58]	⊕	58.7%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.05 [-0.41, 0.51]	⊕	50.9%
Short-Cycle Tertiary (ISCED 5) Completion	0.01 [-0.41, 0.44]	●	43.2%
Short-Cycle Tertiary (ISCED 5) Participation	-0.01 [-0.54, 0.49]	●	40.1%
Bachelor's Degree (ISCED 6) Completion	0.03 [-0.43, 0.49]	●	46.3%
Bachelor's Degree (ISCED 6) Participation	-0.32 [-0.65, 0.00]	⊖⊖⊖	1.3%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Impact of Behavioural Skills Training

Behavioural skills training focuses on instilling positive work habits, attitudes, and behaviours such as punctuality, appropriate language and dress, professionalism, and adherence to workplace norms and expectations.

Employment and labour market: the probability of impact from behavioural skills training on labour market status is low. It is highest for recent employment (59%). It nonetheless may have a medium-sized impact on improved wages (68%), increased time spent in employment (61%) and hours worked (72%).

Education and skills: Behavioural skills training has a 74% probability of positive effect on apprenticeship participation but low probability that this is a high impact. Its impact is clearer and more probable on secondary school completion and higher education (bachelor's degree) participation.

Table 3 Summary of findings for Behavioural Skills Training

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	-0.05 [-0.23, 0.12]	−	11.3%
Recent Employment	0.08 [-0.22, 0.38]	+	58.5%
Currently Unemployed	0.02 [-0.41, 0.44]	●	37.5%
Currently NEET	0.06 [-0.43, 0.54]	−	33.1%
Employment Compensation			
Labour Earnings	0.04 [-0.13, 0.20]	●	46.5%
Wages	0.15 [-0.27, 0.57]	++	67.6%
Employment Duration			
Period Employed	0.10 [-0.25, 0.45]	+	60.6%
Hours Worked			
Hours Worked	0.14 [-0.16, 0.44]	++	71.8%
Education and Skills			
Apprenticeship participation	0.22 [-0.29, 0.73]	+++	74.2%
Occupational licence obtained	0.05 [-0.47, 0.55]	+	49.4%
Secondary School (ISCED 3) Completion	0.27 [0.10, 0.43]	+++	99.5%
Secondary School (ISCED 3) Participation	-0.04 [-0.56, 0.48]	●	36.7%
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.10 [-0.35, 0.57]	+	59.1%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.03 [-0.50, 0.55]	●	46.1%
Short-Cycle Tertiary (ISCED 5) Completion	-0.04 [-0.54, 0.47]	●	36.3%
Short-Cycle Tertiary (ISCED 5) Participation	-0.01 [-0.54, 0.53]	●	41%
Bachelor's Degree (ISCED 6) Completion	0.03 [-0.43, 0.50]	●	46.7%
Bachelor's Degree (ISCED 6) Participation	0.39 [-0.09, 0.67]	+++	98.9%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, + Low positive impact, − Low negative impact, ++ Medium positive impact, −− Medium negative impact, +++ High positive impact, −−− High negative impact.

Impact of Job specific technical skills (Off-the-Job Training)

Job-specific technical/vocational skills training, delivered in an off-job setting, focuses on equipping participants with specialised knowledge and competencies required for specific occupations or industries.

Employment and labour market: Off-the-job, job-specific technical skills training is likely to have a positive effect on current NEET status. It has some effect on employment compensation, with this most likely to be observed on wages. There is low probability that it positively impacts on employment duration or hours worked.

Education and skills: Off-the-job, job-specific technical skills training has high probability of a positive impact on secondary school completion (77%). To a lesser extent, it can positively impact on occupational licence attainment and higher education (bachelor's degree) participation.

Table 4 Summary of findings for Job specific technical skills (Off-the-Job Training)

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	-0.01 [-0.11, 0.09]	●	12.1%
Recent Employment	-0.14 [-0.34, 0.07]	−−	3.4%
Currently Unemployed	0.69 [0.25, 1.12]	−−−	0.0%
Currently NEET	-0.10 [-0.61, 0.40]	+	58.4%
Employment Compensation			
Labour Earnings	0.05 [-0.07, 0.17]	+	52.2%
Wages	0.11 [-0.04, 0.27]	++	78.4%
Employment Duration			
Period Employed	0.03 [-0.19, 0.25]	●	43.1%
Hours Worked			
Hours Worked	-0.08 [-0.37, 0.20]	−	17.8%
Education and Skills			
Occupational licence obtained	0.22 [-0.25, 0.71]	+++	75.3%
Secondary School (ISCED 3) Completion	0.15 [0.03, 0.28]	++	94.4%
Secondary School (ISCED 3) Participation	0.05 [-0.45, 0.56]	+	50.1%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.18 [-0.16, 0.54]	⊕⊕	77.6%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.09 [-0.40, 0.59]	⊕	57.0%
Short-Cycle Tertiary (ISCED 5) Completion	0.03 [-0.42, 0.49]	●	47.2%
Short-Cycle Tertiary (ISCED 5) Participation	0.15 [-0.36, 0.64]	⊕⊕	65.2%
Bachelor's Degree (ISCED 6) Completion	0.15 [-0.25, 0.55]	⊕⊕	69.8%
Bachelor's Degree (ISCED 6) Participation	0.06 [-0.07, 0.19]	⊕	56.0%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Self-Employment Support interventions

Impact of Self-Employment Support

Self-employment support aims to provide advisory services and facilitate access to support, finance and markets for the development or growth of youth-owned businesses or self-employment ventures.

Employment and labour market: Self-employment support has a very high likelihood of high positive impacts on current self-employment and in reducing unemployment. It also reduces likelihood of regular employment, and accordingly, employment duration.

Education and skills: Self-employment support does not support positive impact on secondary school completion. No other education or skills outcomes are reported in the evidence examined.

Table 5 Summary of findings for Self-Employment Support

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	-0.99 [-1.22, -0.76]	−−−	0%
Recent Employment	-0.37 [-0.71, -0.03]	−−−	0.8%
Currently Self-Employed	2.23 [1.97, 2.47]	+++	100%
Currently Unemployed	-0.95 [-1.21, -0.69]	+++	100%
Employment Duration			
Period Employed	-0.65 [-0.90, -0.40]	−−−	0%
Education and Skills			
Secondary School (ISCED 3) Completion	-0.56 [-0.90, -0.23]	−−−	0%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, + Low positive impact, − Low negative impact, ++ Medium positive impact, −− Medium negative impact, +++ High positive impact, −−− High negative impact.

Employment Support interventions

Impact of Job Search Preparation

Job search preparation focuses on equipping young people with the tools and skills needed to effectively navigate the job search process such as developing CVs, cover letters, and online profiles showcasing skills and experience.

Employment and labour market: Job search preparation has a medium to high probability of positively having an impact on reducing NEET (85%). There is little evidence that Job Search Preparation improves employment compensation, although it may slightly increase time spent in employment and has some chance of increasing hours worked (42%).

Education and skills: Job search preparation does not have an impact on education and skills outcomes.

Table 6 Summary of findings for Job Search Preparation

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.03 [-0.08, 0.14]	●	35.5%
Recent Employment	-0.03 [-0.24, 0.19]	●	24.4%
Currently Unemployed	0.21 [-0.02, 0.45]	− − −	1.3%
Currently NEET	-0.27 [-0.68, 0.16]	+ + +	84.5%
Employment Compensation			
Labour Earnings	0.01 [-0.11, 0.13]	●	25.9%
Wages	-0.10 [-0.56, 0.35]	−	26.8%
Employment Duration			
Period Employed	0.10 [-0.11, 0.32]	+	69.7%
Hours Worked			
Hours Worked	0.01 [-0.36, 0.39]	●	42.6%
Education and Skills			
Apprenticeship participation	-0.01 [-0.51, 0.49]	●	40.9%
Occupational licence obtained	0.03 [-0.45, 0.52]	●	46.8%
Secondary School (ISCED 3) Completion	-0.04 [-0.20, 0.12]	●	14.1%
Secondary School (ISCED 3) Participation	0.11 [-0.40, 0.61]	+ +	59.9%
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.03 [-0.47, 0.52]	●	46.0%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.05 [-0.39, 0.48]	+	49.6%
Short-Cycle Tertiary (ISCED 5) Completion	0.02 [-0.44, 0.47]	●	44.0%
Short-Cycle Tertiary (ISCED 5) Participation	0.17 [-0.24, 0.58]	+ +	71.0%
Bachelor's Degree (ISCED 6) Completion	-0.03 [-0.46, 0.39]	●	36.3%
Bachelor's Degree (ISCED 6) Participation	-0.25 [-0.46, -0.03]	− − −	0.2%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, + Low positive impact, − Low negative impact, + + Medium positive impact, − − Medium negative impact, + + + High positive impact, − − − High negative impact.

Impact of Job Search Assistance

Job search assistance provides targeted support to help young people identify and pursue suitable employment and may include job fairs, employer networks, and personalised assistance in finding work well-matched to skills and motivation.

Employment and labour market: findings indicate that Job Search Assistance does not have an impact on labour force status, employment compensation, employment duration or hours worked.

Education and skills: There is low likelihood or uncertainty about Job Search Assistance affecting most education outcomes other than for higher education (bachelor's degree) participation.

Table 7 Summary of findings for Job Search Assistance

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	-0.02 [-0.12, 0.08]	●	8.4%
Recent Employment	-0.03 [-0.27, 0.19]	●	24.2%
Currently Unemployed	0.21 [0.03, 0.38]	−−−	0.3%
Currently NEET	0.20 [-0.24, 0.64]	−−	12.8%
Employment Compensation			
Labour Earnings	0.02 [-0.08, 0.12]	●	27.1%
Wages	0.12 [-0.20, 0.44]	++	66.9%
Employment Duration			
Period Employed	-0.06 [-0.23, 0.11]	−	10.3%
Hours Worked			
Hours Worked	0.03 [-0.35, 0.39]	●	45.1%
Education and Skills			
Apprenticeship participation	-0.01 [-0.54, 0.51]	●	40.6%
Occupational licence obtained	-0.14 [-0.58, 0.30]	−−	20.3%
Secondary School (ISCED 3) Completion	0.03 [-0.11, 0.16]	●	36.7%
Secondary School (ISCED 3) Participation	0.12 [-0.37, 0.62]	++	60.6%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.06 [-0.25, 0.38]	⊕	52.0%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.03 [-0.51, 0.56]	●	46.8%
Short-Cycle Tertiary (ISCED 5) Completion	0.12 [-0.37, 0.61]	⊕⊕	61.1%
Short-Cycle Tertiary (ISCED 5) Participation	-0.01 [-0.54, 0.52]	●	41.4%
Bachelor's Degree (ISCED 6) Completion	-0.04 [-0.52, 0.43]	●	34.4%
Bachelor's Degree (ISCED 6) Participation	0.40 [0.12, 0.67]	⊕⊕⊕	99.3%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Impact of Employment Counselling

Employment counselling offers young people guidance sessions with trained counsellors to assess their skills and interests and explore suitable employment options. These help identify potential career paths and develop plans to pursue this goal.

Employment and labour market: Employment Counselling has high probability of high impact on unemployment reduction. It also has a positive effect on increasing current employment. It may have some low impact on earnings. It is likely to increase time spent in employment but does not affect hours worked.

Education and skills: while most education outcomes are likely to be low or uncertain, Employment Counselling may increase higher education (bachelor's degree) participation.

Table 8 Summary of findings for Employment Counselling

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.06 [-0.04, 0.16]	⊕	56.2%
Recent Employment	-0.02 [-0.25, 0.21]	●	26.9%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Currently Unemployed	-0.16 [-0.45, 0.13]	⊕⊕	77.8%
Currently NEET	0.06 [-0.37, 0.49]	⊖	30.7%
Employment Compensation			
Labour Earnings	0.06 [-0.05, 0.16]	⊕	55.5%
Wages	-0.08 [-0.45, 0.29]	⊖	25.7%
Employment Duration			
Period Employed	0.13 [-0.08, 0.33]	⊕⊕	76.7%
Hours Worked			
Hours Worked	-0.22 [-0.64, 0.22]	⊖⊖⊖	11.4%
Education and Skills			
Apprenticeship participation	-0.01 [-0.52, 0.48]	●	40.5%
Occupational licence obtained	-0.02 [-0.45, 0.42]	●	37.2%
Secondary School (ISCED 3) Completion	-0.06 [-0.21, 0.10]	⊖	9.5%
Secondary School (ISCED 3) Participation	0.12 [-0.30, 0.54]	⊕⊕	63.5%
Post-Secondary Non-Tertiary (ISCED 4) Completion	-0.03 [-0.50, 0.43]	●	36.4%
Post-Secondary Non-Tertiary (ISCED 4) Participation	-0.04 [-0.48, 0.40]	●	33.6%
Short-Cycle Tertiary (ISCED 5) Completion	0.02 [-0.43, 0.48]	●	44.5%
Short-Cycle Tertiary (ISCED 5) Participation	0.00 [-0.49, 0.49]	●	42.2%
Bachelor's Degree (ISCED 6) Completion	-0.07 [-0.52, 0.37]	⊖	30.7%
Bachelor's Degree (ISCED 6) Participation	0.12 [-0.11, 0.35]	⊕⊕	73.0%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Impact of Employment Coaching

Employment coaching services provide access to guidance and support during the application and selection process including interview preparation, coaching on workplace etiquette, and guidance on starting a new job.

Employment and labour market: Employment Coaching can lead to high impact on current NEET status, with a 96% probability of a positive effect. It is unlikely to have a positive effect on other outcomes.

Education and skills: this intervention does not have any positive impacts on education and skills outcomes.

Table 9 Summary of findings for Employment Coaching

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.01 [-0.06, 0.09]	●	15.5%
Recent Employment	0.07 [-0.15, 0.27]	+	57.4%
Currently Unemployed	0.01 [-0.26, 0.29]	●	33.6%
Currently NEET	-0.40 [-0.81, 0.00]	+ + +	95.8%
Employment Compensation			
Labour Earnings	0.02 [-0.06, 0.10]	●	20.1%
Wages	-0.12 [-0.48, 0.24]	− −	17.2%
Employment Duration			
Period Employed	-0.01 [-0.22, 0.19]	●	28.6%
Hours Worked			
Hours Worked	-0.04 [-0.42, 0.34]	●	31.8%
Education and Skills			
Apprenticeship participation	0.04 [-0.45, 0.51]	●	47.6%
Occupational licence obtained	0.01 [-0.35, 0.37]	●	40.9%
Secondary School (ISCED 3) Completion	-0.08 [-0.22, 0.05]	−	3.0%
Secondary School (ISCED 3) Participation	0.04 [-0.43, 0.50]	●	47.9%
Post-Secondary Non-Tertiary (ISCED 4) Completion	-0.03 [-0.48, 0.41]	●	35.3%
Short-Cycle Tertiary (ISCED 5) Completion	-0.04 [-0.49, 0.41]	●	34.2%
Short-Cycle Tertiary (ISCED 5) Participation	-0.01 [-0.50, 0.49]	●	41.4%
Bachelor's Degree (ISCED 6) Completion	-0.04 [-0.41, 0.34]	●	32.6%
Bachelor's Degree (ISCED 6) Participation	-0.25 [-0.39, -0.12]	− − −	0.0%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ⚪ Little or no effect, ➕ Low positive impact, ➖ Low negative impact, ➕➕ Medium positive impact, ➖➖ Medium negative impact, ➕➕➕ High positive impact, ➖➖➖ High negative impact.

Impact of Financial Assistance

Financial assistance services provide targeted support to help young people overcome financial barriers that hinder their search for employment. These may include coverage of transport costs to interviews, professional attire, or job-related expenses (such as cost coverage for industry accreditations necessary to secure work).

Employment and labour market: The probability of any positive impact is high for Recent Employment (84%), but low for other outcomes. Overall, Financial Assistance has a reasonable probability of positive impact on recent employment and current employment. There is little evidence that it improves earnings or wages, or time in employment. It is likely to have a reasonable chance of increasing hours worked.

Education and skills: there is no meaningful effect on apprenticeship participation or secondary school completion, but financial assistance may improve likelihood to achieve occupational licence.

Table 10 Summary of findings for Financial Assistance

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.03 [-0.06, 0.15]	⚪	35.9%
Recent Employment	0.13 [-0.03, 0.29]	➕➕	83.4%
Currently Unemployed	1.52 [1.16, 1.87]	➖➖➖	0.0%
Currently NEET	0.06 [-0.28, 0.40]	➖	26.8%
Employment Compensation			
Labour Earnings	-0.06 [-0.17, 0.06]	➖	3.7%
Wages	-0.25 [-0.62, 0.11]	➖➖➖	5.3%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Employment Duration			
Period Employed	0.00 [-0.26, 0.24]	●	34.6%
Hours Worked			
Hours Worked	0.07 [-0.13, 0.28]	⊕	59.3%
Education and Skills			
Apprenticeship participation	-0.05 [-0.53, 0.42]	⊖	33.1%
Occupational licence obtained	0.20 [-0.26, 0.66]	⊕⊕	74.1%
Secondary School (ISCED 3) Completion	0.09 [-0.04, 0.24]	⊕	74.0%
Secondary School (ISCED 3) Participation	0.05 [-0.49, 0.58]	⊕	50.2%
Post-Secondary Non-Tertiary (ISCED 4) Completion	-0.18 [-0.65, 0.28]	⊖⊖	16.5%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.10 [-0.43, 0.60]	⊕	57.2%
Short-Cycle Tertiary (ISCED 5) Completion	0.15 [-0.27, 0.57]	⊕⊕	68.3%
Short-Cycle Tertiary (ISCED 5) Participation	0.15 [-0.34, 0.62]	⊕⊕	64.7%
Bachelor's Degree (ISCED 6) Completion	-0.14 [-0.65, 0.37]	⊖⊖	24.0%
Bachelor's Degree (ISCED 6) Participation	0.05 [-0.19, 0.29]	⊕	49.1%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Employment experience interventions

Impact of Job-specific technical skills (On-the-Job training)

These programmes have an occupational focus and long durations (6+ months). Roles are temporary and may not be paid if young people receive welfare benefits or other government funding. Young people are placed with employers to undertake tasks of a competitive job and gain specific technical and soft skills. The young person will spend most of their time with the employer.

Employment and labour market: findings suggest that Job Specific Technical Skills (On-the-Job Training) has a greater than even probability (63%) of having a positive effect

on current employment, a very high probability on wages (84%) and earnings (96%). It may also improve employment duration, but is unlikely to improve hours worked.

Education and skills: any effect on education and skills outcomes is low or uncertain except for apprenticeship participation which Job Specific Technical Skills (On-Job Training) may increase.

Table 11 Summary of findings for Job-specific technical skills (On-the-Job training)

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.06 [-0.03, 0.15]	+	62.5%
Recent Employment	0.01 [-0.17, 0.18]	●	32.1%
Currently Self-Employed	-0.04 [-0.36, 0.28]	●	29.6%
Currently Unemployed	0.12 [-0.06, 0.31]	− −	3.6%
Currently NEET	-0.05 [-0.52, 0.40]	+	50.9%
Employment Compensation			
Labour Earnings	0.15 [0.04, 0.26]	+ +	95.8%
Wages	0.16 [-0.06, 0.37]	+ +	84.1%
Employment Duration			
Period Employed	0.10 [-0.06, 0.26]	+	73.7%
Hours Worked			
Hours Worked	-0.02 [-0.34, 0.30]	●	34.1%
Education and Skills			
Apprenticeship participation	0.20 [-0.24, 0.64]	+ +	74.3%
Occupational licence obtained	-0.08 [-0.49, 0.34]	−	26.8%
Secondary School (ISCED 3) Completion	-0.02 [-0.21, 0.16]	●	20.7%
Secondary School (ISCED 3) Participation	0.06 [-0.34, 0.44]	+	51.4%
Post-Secondary Non-Tertiary (ISCED 4) Completion	0.03 [-0.46, 0.52]	●	46.4%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.03 [-0.36, 0.42]	●	46.6%
Short-Cycle Tertiary (ISCED 5) Completion	0.08 [-0.39, 0.54]	+	54.2%
Short-Cycle Tertiary (ISCED 5) Participation	-0.01 [-0.52, 0.52]	●	41.3%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Bachelor's Degree (ISCED 6) Completion	-0.03 [-0.52, 0.44]	⚪	36.9%
Bachelor's Degree (ISCED 6) Participation	-0.09 [-0.20, 0.03]	➖	1.2%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ⚪ Little or no effect, ➕ Low positive impact, ➖ Low negative impact, ➕➕ Medium positive impact, ➖➖ Medium negative impact, ➕➕➕ High positive impact, ➖➖➖ High negative impact.

Impact of Paid Temporary Work Experience

The duration of paid temporary work experience tends to be short as the purpose is to build insights into the world of work and allow 'practise' of the behavioural skills needed to sustain work.

Employment and labour market: findings indicate that Paid Temporary Work Experience can have a positive impact on labour market status, particularly through reducing current unemployment (96%). The probability of a medium or high impact is high for Currently Unemployed (88%). Paid temporary work experience does not appear to improve earnings or wages, employment duration or hours worked.

Education and skills: this intervention has a low likelihood of creating impacts for education outcomes with two exceptions: higher education (bachelor's degree) and short course/cycle tertiary completion.

Table 12 Summary of findings for Paid Temporary Work Experience

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.03 [-0.07, 0.13]	⚪	31.5%
Recent Employment	0.04 [-0.14, 0.21]	⚪	44.1%
Currently Unemployed	-0.21 [-0.39, -0.03]	➕➕➕	96.0%
Currently NEET	0.09 [-0.31, 0.48]	➖	23.7%
Employment Compensation			
Labour Earnings	-0.08 [-0.19, 0.02]	➖	0.7%

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Wages	-0.11 [-0.32, 0.10]	−−	6.8%
Employment Duration			
Period Employed	-0.08 [-0.23, 0.07]	−	5.2%
Hours Worked			
Hours Worked	-0.04 [-0.25, 0.16]	○	19.9%
Education and Skills			
Apprenticeship participation	-0.03 [-0.52, 0.47]	○	38.9%
Occupational licence obtained	-0.01 [-0.39, 0.39]	○	38.8%
Secondary School (ISCED 3) Completion	-0.15 [-0.29, -0.01]	−−	0.3%
Secondary School (ISCED 3) Participation	0.02 [-0.37, 0.40]	○	43.4%
Post-Secondary Non-Tertiary (ISCED 4) Completion	-0.18 [-0.66, 0.30]	−−	17.2%
Post-Secondary Non-Tertiary (ISCED 4) Participation	0.00 [-0.38, 0.41]	○	40.4%
Short-Cycle Tertiary (ISCED 5) Completion	0.11 [-0.33, 0.54]	++	61.5%
Short-Cycle Tertiary (ISCED 5) Participation	-0.03 [-0.45, 0.40]	○	36.0%
Bachelor's Degree (ISCED 6) Completion	-0.12 [-0.48, 0.23]	−−	17.3%
Bachelor's Degree (ISCED 6) Participation	0.13 [0.00, 0.26]	++	87.2%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ○ Little or no effect, + Low positive impact, − Low negative impact, ++ Medium positive impact, −− Medium negative impact, +++ High positive impact, −−− High negative impact.

Impact of Unpaid Temporary Work Experience

The duration of unpaid temporary positions also tends to be short. It shares purpose with paid temporary work to build insights into the world of work and enable to 'practise' the behavioural skills needed to sustain work.

Employment and labour market: Findings indicate high impacts that are almost certain and highly probable respectively for increases Currently Employed and reductions in NEET. Overall, it is likely that unpaid temporary work experience has a positive impact on labour market status. It also has a reasonable probability of positive impact on wages, but is unlikely to increase employment duration or hours worked.

Education and skills: Unpaid Temporary Work Experience can have a positive impact on education and skills outcomes—particularly bachelor's degree participation.

Table 13 Summary of findings for Unpaid Temporary Work Experience

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	0.34 [0.12, 0.58]	⊕⊕⊕	99.5%
Recent Employment	-0.10 [-0.36, 0.16]	⊖	12.8%
Currently Unemployed	0.67 [0.24, 1.11]	⊖⊖⊖	0.1%
Currently NEET	-0.45 [-0.92, 0.00]	⊕⊕⊕	95.8%
Employment Compensation			
Labour Earnings	0.00 [-0.19, 0.19]	●	31.2%
Wages	0.14 [-0.24, 0.53]	⊕⊕	68.3%
Employment Duration			
Period Employed	-0.11 [-0.40, 0.18]	⊖⊖	13.8%
Hours Worked			
Hours Worked	-0.07 [-0.48, 0.33]	⊖	28.0%
Education and Skills			
Occupational licence obtained	-0.03 [-0.53, 0.47]	●	38.6%
Secondary School (ISCED 3) Completion	0.09 [-0.12, 0.31]	⊕	65.1%
Bachelor's Degree (ISCED 6) Participation	0.23 [-0.01, 0.49]	⊕⊕⊕	93.0%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Subsidised employment interventions

Impact of Wage Subsidies

Wage subsidies offer financial incentives to employers to employ disadvantaged young people. Subsidies can include direct payments, tax breaks, or tax credits. The primary aim is to help disadvantaged individuals secure longer-term employment by reducing financial risks to employers.

Employment and labour market: estimates fall within the low impact range, but probability of impact is >50% for Recent Employment (56%), Currently Unemployed (54%) and Currently NEET (50%). There is little evidence for any effect on wages and earnings, time spent in employment or hours worked.

Education and skills: there is evidence for an effect of Wage Subsidies on secondary school completion, with a 76% probability of an effect favouring the intervention.

Table 14 Summary of findings for Wage Subsidies

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Employed	-0.12 [-0.33, 0.07]	−	3.6%
Recent Employment	0.07 [-0.21, 0.36]	+	55.8%
Currently Unemployed	-0.06 [-0.31, 0.20]	+	53.7%
Currently NEET	-0.05 [-0.53, 0.41]	+	50.0%
Employment Compensation			
Labour Earnings	-0.05 [-0.29, 0.20]	−	22.1%
Wages	-0.02 [-0.28, 0.24]	●	29.1%
Employment Duration			
Period Employed	0.01 [-0.19, 0.22]	●	36.1%
Hours Worked			
Hours Worked	-0.03 [-0.28, 0.23]	●	27.0%
Education and Skills			
Apprenticeship participation	-0.02 [-0.52, 0.46]	●	38.4%
Secondary School (ISCED 3) Completion	0.15 [-0.13, 0.45]	++	75.9%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, + Low positive impact, − Low negative impact, ++ Medium positive impact, −− Medium negative impact, +++ High positive impact, −−− High negative impact.

Impact of Public works

Public works programmes are government-initiated employment schemes aimed at providing temporary employment through infrastructure development, maintenance, and other community service projects. Public works programmes directly employ

individuals. Public works programmes are often implemented when there is not enough labour demand and so form a temporary safety net.

Employment and labour market: included studies only measure the impact on reducing current unemployment for which the probability of any impact is 62%. Nonetheless, findings suggest that Public Works can reduce unemployment at 24 months more than half the time. Any effect on wages is limited and uncertain. There does not appear to be an effect on employment duration.

Education and skills: no education or skills outcomes are documented for this intervention.

Table 15 Summary of findings for Public Works

OUTCOME	MEDIAN EFFECT SIZE (95% CREDIBLE INTERVAL)	MAGNITUDE OF MEDIAN EFFECT SIZE	PROBABILITY OF MEANINGFUL POSTIVE EFFECT
Labour Force Status			
Currently Unemployed	-0.13 [-0.68, 0.41]	⊕⊕	61.80%
Employment Compensation			
Wages	0.06 [-0.32, 0.44]	⊕	51.50%
Employment Duration			
Period Employed	-0.03 [-0.41, 0.34]	●	34.40%

Note: Effect size thresholds are defined in Table 19; Meaningful effect is defined as $g > 0.05$.
Key: ● Little or no effect, ⊕ Low positive impact, ⊖ Low negative impact, ⊕⊕ Medium positive impact, ⊖⊖ Medium negative impact, ⊕⊕⊕ High positive impact, ⊖⊖⊖ High negative impact.

Conclusions and next steps

While this review provides a high-level synthesis of relative effectiveness of 15 intervention components across seven outcome domains, the current findings represent a foundation from which more granular analyses can be developed. There is significant scope to move beyond aggregate effects by utilisng the existing network to test specific hypotheses regarding the interaction between intervention components and further explore heterogeneity. Furthermore, the stability of these estimates remains to be tested against critical moderators, including participant demographics and macro-economic contexts such as business cycle dynamics.

Background & Context

Challenges facing young people entering the labour market

Securing good quality employment is a key marker in young people's transition to adulthood and an instrumental determinant of good health in adulthood and later life. Achieving meaningful employment without lengthy delays due to unemployment and inactivity, allows young people to develop human capital which assists them throughout their working life as well as developing their identity, sense of purpose and economic independence (Grosemans *et al.*, 2020; Naval, Silva and Vázquez-Grenno, 2020). In addition, there is evidence that unemployment and inactivity at a young age are actively harmful to health and future prospects due in part to loss of skills and poor mental health (Bell and Blanchflower, 2011; Strandh *et al.*, 2014). Globally, more than one-fifth (20.4%) of young people were not in education, employment, or training (NEET) in 2023 (International Labour Organization, 2025). In high-income countries, the unemployment rate in 2024 was 11.6%, which is a return to the pre-COVID levels following a high of 14.5% in 2020 (International Labour Organization, 2025). The rate of young people NEET in the UK by the end of 2024 was higher, at 13.18%. The UK has struggled in contrast to other high-income countries to see a return to pre-pandemic rates of labour market participation across its population.

Individual and population-level barriers to labour market entry

Young people face unique challenges when seeking to enter and remain in the labour market, such as limited skills, qualifications, and work experience. They are more vulnerable to exogenous shocks, such as the global financial crisis and COVID-19 pandemic (Bell and Blanchflower, 2011). When unemployment is high, they find it hard to compete against slightly older, more experienced and better qualified people (Atkinson and Williams, 2003). Over the period since the COVID-19 pandemic, the incidence of young people being inactive in the United Kingdom (UK) due to poor health has shown a significantly rising trend. This is recognised in the Get Britain Working White Paper which brings together a range of measures to address youth (and wider) employment and inactivity, which is increasingly caused by ill-health, and particularly poor mental health among young people (HM Government, 2024). Accordingly, the Keep Britain Working Review discovery report similarly highlights "a surge in the number of people with work-limiting health conditions between 2015 and 2024... [with] the largest increases observed among younger people (aged 16 to 34) with an increase of 1.2 million or 77%" (Mayfield, 2025). It notes that youth economic inactivity is driven by poor mental health. Evidence from the Children's Commissioner (2024) indicates a rising

trend in reported psychological distress among school-aged children. NHS (2023) figures show the prevalence of probable mental health conditions increased from one in eight children in 2017 to one in five by 2023. This trend is particularly pronounced in young women; by age 17, the prevalence rate is approximately double that of young men. Despite increased funding, the Children's Commissioner notes that service capacity has not kept pace with demand. These findings contextualise the challenges facing young people as they enter a labour market defined by falling vacancies and heightened competition. Given the scale and implications of this challenge for individual and societal economic and social outcomes, the government has launched the Youth People and Work Report (2025) to assess evidence for the causes of this trend for rising rates of NEET, and the relationship with health as well as the practices and interventions that could overcome it (Bell and Blanchflower, 2011; Coles et al, 2010).

These poorer outcomes do not spread evenly across the young population. Disadvantaged young people and those with limited skills and qualifications have worse employment outcomes (Lindsay *et al.*, 2022; Harrison *et al.*, 2023). Those from minoritised ethnic groups including black and Bangladeshi young people are over-represented in the NEET group in the UK (Youth Futures Foundation, 2026). Disabled young people and those with long-term health conditions are less likely to be employed than their peers (Work and Pensions Committee, 2023).

Structural and demand-side labour market pressures

Structural economic factors also affect youth employment rates. UK Government projections see the largest additional employment between 2025-30 in creative industries, digital and technologies, housebuilding and clean energy. Among priority occupations, demands for more highly qualified people are increasing with two thirds of additional employment demand in priority occupations projected to require people with skills at level 4 and above (Skills England, 2025). Over time, there may be diminishing demand for entry level and lower skill levels. Other analysis indicates rising demand from employers for key essential skills covering communication, collaboration, problem-solving, organising, planning & prioritising work, creative thinking and 'information literacy' (skills related to gathering, processing, and using information) indicating key areas where young people need to be prepared for labour market entry (Dickerson *et al.*, 2023).

Taken together, these individual-level constraints and structural labour market shifts compound one another, disproportionately hindering labour market entry and progression for disadvantaged young people.

Policy responses: active labour market programmes

A wide range of policies, programmes, and interventions have been deployed to support young individuals to acquire the skills and experience needed to join and sustain a position within the workforce. Many of these initiatives fall under the umbrella of Active Labour Market Programmes (ALMPs), which can encompass skills training, expenditure on public employment services and their administration, job search training, programmes focused on assisting young people through their transition from school to work, employment incentives, wage subsidies, support for business start-ups, and rehabilitation services (Kluve *et al.*, 2017; OECD, 2021).

By definition, ALMPs incorporate activation strategies, which aim to encourage or compel unemployed individuals to actively seek work or enhance their employability, based on the principle that this engagement can lead to better labour market outcomes. These programmes often feature conditional elements, where receipt of unemployment or social assistance benefits is tied to fulfilling specific obligations such as job search requirements or participation in training programmes, reflecting a 'mutual obligations' approach to welfare provision.

Purpose and scope of this review

Existing evidence on the effectiveness of ALMPs for young people

Previous reviews have examined the effectiveness of ALMPs for young people using various approaches. Card et al. (2010, 2018) conducted meta-analyses twice, finding that ALMPs had no impact on employment outcomes in the short term but had positive impacts in the medium term, with larger gains observed amongst programmes that sought to improve human capital. Kluve et al. (2017) focusing on young people aged 15–35, reported positive effects on employment and earnings for interventions that included skills development and entrepreneurship support, with larger impacts observed in programmes targeting disadvantaged youth and those implemented in low- and middle-income countries.

Puerto et al. (2022) updated this systematic review and reinforced the presence of substantial heterogeneity in ALMP impacts across contexts. Their findings indicated that programme effectiveness varied systematically between high-income and low- and middle-income countries, as well as by programme design and target population. In high-income settings, positive effects were more commonly observed for interventions incorporating skills training and those delivered by public agencies or at sub-national levels, while across settings, stronger impacts were more likely among younger

participants and disadvantaged groups. Collectively, these reviews have focused on estimating the effects of bundled programmes, particularly where interventions are targeted at disadvantaged young people in high-income countries.

These prior reviews by Card (2010, 2018), Kluve et al. (2017) and Puerto et al. (2022) sought to identify the effectiveness of packages of support, particularly where in high income countries these are targeted at the most disadvantaged. In contrast, a previous review conducted by members of this review team (Taylor *et al.*, 2023) adopted a component-based network meta-analysis approach to disaggregate selected employment- and skills-focused programme types into their constituent intervention components, with the aim of estimating the impact of these components on employment and education outcomes. That review identified heterogeneity in impacts across components, with evidence that some intervention elements were more effective for young people facing disadvantage. While limited in scope, the review demonstrated the feasibility and value of examining the impact of intervention components.

Contribution and scope of the current review

The current review builds on and extends earlier syntheses conducted by members of this review team, including the component network meta-analysis (CNMA) of employment and skills programs (Taylor *et al.*, 2023) and a meta-analysis of wage subsidies (Nancarrow *et al.*, 2023). It substantially expands the scope of the previous review by incorporating the results of updated searches used by Puerto et al. (2022), and an (October 2023) update to the evidence and gap map (EGM) by Apunyo et al. (2022). It also broadens the scope of included intervention components to encompass the full range of different types of ALMPs provided in high-income countries, and provides more granular coverage of outcomes, including labour force status, employment compensation, period employed, hours worked and education and skills.

This review was commissioned by the Youth Futures Foundation (YFF) to inform an update to YFF's Youth Employment Toolkit. The remainder of this report is structured as follows. The methodology section sets out the review's objectives, scope, data sources, and analytic approach. The results are presented in dedicated chapters reporting component-level impacts by intervention type. The discussion interprets these findings and considers their implications, including priorities for future research and evidence development.

Methodology

Objectives

The objective of this review and meta-analysis was to assess the impact of components of Active Labour Market Programmes (ALMPs) on employment and education outcomes for young people (aged 15-35) in high-income countries.

The research questions that guided our review and the current analysis were:

1. What is the impact of individual components of active labour market programmes on **labour market outcomes** for young people aged 15-35 in high-income countries, compared to services as usual?
2. What is the impact of individual components of active labour market programmes on **education and skills outcomes** for young people aged 15-35 in high-income countries, compared to services as usual?

Study eligibility criteria

Our inclusion and exclusion criteria are listed for each Population, Intervention, Comparison, Outcome, Setting and Study Design (PICOSS) (Huang, Lin and Demner-Fushman, 2006) domain below.

Population

Inclusion criteria

Young people and emerging adults (15-35 years old).

This was defined by:

- if the intervention's target or served population falls within the range 15–35 years; or
- if the study reports a subgroup analysis[1] for participants aged 15–35; or

[1] Puerto et al. (2022) only included ALMPs that were specifically targeted at a youth population, whereas Kluve et al. (2014, 2017) included general population ALMPs where a subgroup analysis was available for a youth population. We have followed the approach by Kluve et al. (2017) and included any study that includes a relevant subgroup analysis.

- If a study satisfies one of the following criteria: (a) the mean and ± 1 standard deviation (SD) of the mean population age falls fully within the 15–35 age range; (b) if the SD of the mean age is not reported, when the mean age falls within the range is 22–27 years.

Exclusion criteria

Individuals aged less than 15 and greater than 35.

This included:

- mixed age group samples including over 35s or under 16s, without data for those in the 15-35 age range presented separately, and
- any study whose mean and SD (or mean alone) for age does not meet the criteria specified above.

Intervention

We applied a definition of ALMP that aligns directly with that used by the Puerto et al. (2022) review. Their review, in turn, built directly on the search strategy and definitions specified in the Kluve et al. (2014) review protocol — which cited the following definition from the OECD:

"[ALMP are] all social expenditure (other than education) which is aimed at the improvement of the beneficiaries' prospect of finding gainful employment or to otherwise increase their earnings capacity. This category includes spending on public employment services and administration, labour market training, special programmes for youth when in transition from school to work, labour market programmes to provide or promote employment for unemployed and other persons (excluding young and disabled persons) and special programmes for the disabled."

The Puerto et al. (2022) review divided ALMP into five overarching interventions: skills development, entrepreneurship promotion, employment services, wage subsidies and public works. For the present review, we retained the five-domain structure but refined the sub-classification to better capture intervention heterogeneity. Specifically, we divided programmes into five overarching interventions, each comprising multiple components, resulting in a taxonomy of 17 active components[2] (see Table 16).

[2] We coded ALMPs that contained additional components that fell outside the scope of these definitions, but may still have an impact on participant outcomes, as a residual 'other' component.

Inclusion criteria:

ALMPs that include one or more of the following intervention components:

- *Skills Development* — (a) Basic Skills Training; (b) Soft Skills Training; (c) Behavioural Skills Training; or (d)Job-specific technical skills (off-job) training
- *Self-employment support* — (a) Business Skills Training; (b) Business Advisory and Mentoring; (c) Financial and start-up support
- *Employment services* — (a) Job Search Preparation; (b) Job Search Assistance; (c) Employment Counselling; (d)Employment Coaching; or (e) Financial Assistance.
- *Employment experience* — (a) Job-specific technical skills (on-job); (b) Paid temporary work experience; (c)Unpaid temporary work experience
- Subsidised employment — (a) Wage Subsidies; or (b) Public Works

Exclusion criteria:

Interventions were excluded if they solely included other components.

Table 16 Intervention and component definitions

INTERVENTION		COMPONENT	
NAME	**DEFINITION**	**NAME**	**DEFINITION**
Skills development	Skills development includes training programmes offered outside the formal education system to enhance youth employability or facilitate the transition into employment. The training takes place outside a work environment and before the transition to employment. This review has divided this element of ALMP into four components: basic skills training; soft skills training; behavioural skills training and job-specific technical skills (off-job) training.	**Basic Skills Training**	Basic skills training focuses on enhancing foundational competencies such as literacy, numeracy, and digital skills that are essential for individuals to effectively engage in education, training, or employment. These programmes aim to bridge skill gaps from the compulsory education phase and equip participants with the necessary abilities to navigate personal and professional environments successfully. Basic skills training is often targeted towards individuals who may have had limited formal education.
		Soft Skills Training	Soft skills training concentrates on developing interpersonal skills. These programmes emphasise building competencies in areas such as communication, teamwork, collaboration, problem-solving, decision-making, critical thinking, and analysis.
		Behavioural Skills Training	Behavioural skills training focuses on instilling positive work habits, attitudes, and behaviours that are crucial for success in the workforce. These programmes cover aspects such as punctuality, appropriate language, dress and communication, professionalism, and adherence to workplace norms and expectations.
		Job-specific technical skills (off-job) training	Job-specific technical/vocational skills training, delivered in an off-job setting, focuses on equipping participants with specialised knowledge and competencies required for specific occupations or industries. These programmes adopt a "train first, then place" approach, where individuals receive intensive, often full-time, training in a classroom or educational setting before transitioning into employment.
Self-employment support	Self-employment support aims to provide advisory services and facilitate access to support, finance and markets for the development or growth of youth-owned	**Business Skills Training**	Business skills training focuses on equipping participants with the knowledge and competencies necessary to start, manage, and grow a business or self-employment venture. These programmes cover topics such as business planning, financial management, marketing, sales, and customer service.

INTERVENTION		COMPONENT	
NAME	**DEFINITION**	**NAME**	**DEFINITION**
	businesses or self-employment ventures. These interventions include a range of services such as business advisory and mentoring support, business skills training, access to markets and value chains, direct credit or facilitated access to credit, monetary or in-kind grants for start-up or growth, and micro-franchising initiatives or mechanisms. Self-employment support can focus on entrepreneurship and business innovation or the skills and capabilities to offer craft and service skills through self-employment.	**Business Advisory and Mentoring**	Business advisory and mentoring services provide personalised guidance and support to help participants develop and implement their business or self-employment plans. These services may include one-on-one coaching, group mentoring sessions, and access to networks of experienced entrepreneurs or industry professionals.
		Financial and start-up support	Financial and start-up support provides participants with access to the capital and resources needed to launch and sustain their businesses or self-employment ventures. These interventions may include direct credit, facilitated access to credit through partnerships with financial institutions and monetary or in-kind grants for start-up or growth.
Employment Services	Employment services aim to equip young people with the skills to identify work that is suitable and meaningful to them, search for and secure jobs. In supporting young people these services can offer targeted provision to young people and employers. For young people this includes job-search preparation and assistance, job matching and brokerage. For those most distant from the labour market, employment services may mobilise additional and more extensive support services from subcontractors and the third sector. Employment services often engage with employers to understand their vacancies and skills gaps, with aims to prepare young people to be able to fill these. To support young people's take-up of jobs, financial assistance for travel and expenses may be offered. Employment services will also collaborate with	**Job Search Preparation**	Job search preparation services focus on equipping young jobseekers with the tools and skills necessary to effectively navigate the job search process. These services may include workshops or one-on-one support for crafting professional resumes, cover letters, and online profiles that showcase the jobseeker's skills and experiences.
		Job Search Assistance	Job search assistance services provide targeted support to help young jobseekers identify and pursue suitable employment opportunities. These services may include access to job listings (either online or in-person, public or not-listed), job fairs, and employer networks, as well as personalised assistance in identifying job openings that align with the jobseeker's skills and interests.
		Employment Counselling	Employment counselling offers guidance to help jobseekers to assess their skills and interests, and explore suitable employment options. These services may include one-on-one sessions with trained counsellors who help jobseekers understand the labour market, identify potential career paths, and develop a plan to pursue their desired employment outcomes.

INTERVENTION		COMPONENT	
NAME	**DEFINITION**	**NAME**	**DEFINITION**
	community partners and regional governments to link to wider public services and industry/employer bodies to ensure connection to local labour markets.	**Employment Coaching**	Employment coaching services provide access to guidance and support during the application and selection process. These services may include interview preparation, coaching on workplace communication and etiquette, and guidance on navigating the challenges of starting a new job.
		Financial Assistance	Financial assistance services provide targeted support to help jobseekers overcome financial barriers that hinder their search for employment. These services may include grants or subsidies for transportation costs to interviews, professional attire, or other job-related expenses (e.g., attainment of driving licence or industry credential necessary to secure work) that may otherwise provide a barrier to the jobseeker.
Employment experience	Employment experience is offered to young jobseekers as a form of work-related training before they secure a competitive job. It is intended to be temporary and roles may not be paid. These programmes can include on the job training for technical and soft skills related to an occupation, or provide a more general insight into the world of work. They all involve attendance at an employers' workplace. Some programmes may be undertaken for employers advertising vacancies who guarantee a job interview as part of the package. The duration of programmes can vary considerably between short periods, of one or two weeks, or longer durations for example up to a year. Some programmes are designed to support particularly vulnerable groups, such as	**Job-specific technical skills (on-job)**	These programmes often have an occupational focus and have relatively long durations, up to six months and sometimes more. The roles are temporary and may not be paid, if the young person is receiving social welfare benefits or other government funding. Young people are placed with employers to undertake tasks associated with a competitive job in those employers. The purpose is to provide training in the specific technical and soft skills associated with the occupation. These type employment placements may be complemented by short spells of off-the-job learning but the young person will spend the large majority of their time with the employer.
		Paid temporary work experience	These programmes offer paid temporary positions to young people. The duration tends to be much shorter and the purpose is to build insights into the world of work and to 'practise' the behavioural skills needed to sustain work. This could include internships. Some paid work experience programmes may be for employers advertising vacancies. In this case, the employer may guarantee an interview at the end, which may mean the young person can move into permanent employment.

INTERVENTION		COMPONENT	
NAME	**DEFINITION**	**NAME**	**DEFINITION**
	disabled young people. These typically offer additional support to the young person and employer through case worker support.	**Unpaid temporary work experience**	These programmes offer unpaid temporary positions to young people. The duration tends to be much shorter and the purpose is to build insights into the world of work and to 'practise' the behavioural skills needed to sustain work. This could include internships. Some unpaid work experience programmes may be for employers advertising vacancies. In this case, the employer may guarantee an interview at the end, which may mean the young person can move into permanent employment.
Subsidised employment	Subsidised employment can take place in the private, public and third sectors. There are two main types of subsidised employment: jobs that employment services fund directly with employers, usually in private and third sectors. The aim is to reduce employer hiring risks to encourage them to take on disadvantaged young people. An alternative is to create new short-term jobs in the public sector using government funding. These type programmes are categorised as public works. Both types of program intend to be a short-term measure that enables young people to build the skills and social capital to secure competitive, unsubsidised employment.	**Wage Subsidies**	Wage subsidies are financial incentives provided to employers to support the employment of disadvantaged young jobseekers. The subsidies can take the form of direct payments, tax breaks, reduced payroll taxes, reduced social security contributions, or tax credits. The primary aim is to help individuals secure longer-term employment by reducing the financial risks to employers who perceive disadvantaged young people's productivity will be below market standards. The ultimate goal is to facilitate immediate employment and then encourage sustained employment by lowering employment costs for employers and enhancing the employability of the jobseeker.
		Public Works	Public works programmes are government-initiated employment schemes aimed at providing temporary employment through infrastructure development, maintenance, and other community service projects. Public works programmes directly employ individuals through government projects, whereas wage subsidies incentivise private and third sector employers to hire individuals by offsetting some of the employment costs. Public works programmes are often considered a solution in times of crises, when there is not enough labour demand and thus as a temporary safety net.

Comparison

Inclusion criteria

Studies where the comparison group is provided with usual services, no intervention, other services, or wait-list control. Studies were not required to include a usual services arm; studies directly comparing two or more eligible ALMP components or component combinations were eligible.

Exclusion criteria

Studies where the comparison group is provided with another comparison or is not a valid comparator (i.e., the population is completely confounded with one condition).

Outcomes

Inclusion criteria

We included studies that reported a quantitative measure of:

Primary outcomes

- *Employment outcomes* — including: employment, unemployment, hours worked, employment duration or employment quality.
- *Earnings outcomes* — including: earnings, salary, hourly wage or income.
- *Business performance outcomes* — including: sales, profits, business creation/survival.

Secondary outcomes

- *Education and skills outcomes* — including: educational attainment, cognitive skill measures (e.g., literacy and numeracy scores), non-cognitive skill assessments and measures of job-specific skills or certification
- *Social networks and relationships outcomes* — including: existence/strength/size of positive work/peer/family relationships
- *Physical and mental health outcomes* — including: physical health, mental health, measures of healthy behaviour (nutrition or substance use) and health literacy and health resilience.

Exclusion criteria

Studies that reported other outcomes were not eligible for inclusion.

Setting

Studies needed to be conducted in high-income countries, as defined by the World Bank (2024)[3].

Study design

Inclusion criteria

This analysis included primary studies that used causal methods to evaluate the impact of ALMPs. These methods estimate effects by comparing observed participant outcomes with hypothetical non-participant outcomes. Included studies employed one of the following approaches:

- *Randomised experiments (RE)* — this class of methods included those designs where treatment allocation is random or plausibly random including randomised controlled trials (RCTs) at the individual or cluster level, stepped-wedge designs and natural experiments.
- *Selection on observables (SOO)* — these methods allow for causal inference under unconfoundedness and included: regression adjustment, statistical matching and weighting (including propensity score matching, inverse probability of treatment weighting and doubly robust methods).
- *Design-based identification (DBI)* — this class of methods included the use of instrumental variables, regression discontinuity design, synthetic control and difference-in-differences (DiD).

[3] These countries are: Aruba, Andorra, United Arab Emirates, American Samoa, Antigua and Barbuda, Australia, Austria, Belgium, Bahrain, Bahamas (The), Bermuda, Barbados, Brunei Darussalam, Canada, Switzerland, Channel Islands, Chile, Curaçao, Cayman Islands, Cyprus, Czechia, Germany, Denmark, Spain, Estonia, Finland, France, Faroe Islands, United Kingdom, Gibraltar, Greece, Greenland, Guam, Guyana, Hong Kong (SAR, China), Croatia, Hungary, Isle of Man, Ireland, Iceland, Israel, Italy, Japan, St. Kitts and Nevis, Korea (Rep), Kuwait, Liechtenstein, Lithuania, Luxembourg, Latvia, Macao (SAR, China), St. Martin (French part), Monaco, Malta, Northern Mariana Islands, New Caledonia, Netherlands, Norway, Nauru, New Zealand, Oman, Panama, Poland, Puerto Rico, Portugal, French Polynesia, Qatar, Romania, Saudi Arabia, Singapore, San Marino, Slovak Republic, Slovenia, Sweden, Sint Maarten (Dutch part), Seychelles, Turks and Caicos Islands, Trinidad and Tobago, Taiwan (China), Uruguay, United States, British Virgin Islands, Virgin Islands (U.S.).

Exclusion criteria

Studies were excluded if they did not constitute primary impact evaluations or did not employ a credible causal identification strategy. This included non-primary studies (e.g., systematic reviews, meta-analyses and literature reviews), as well as qualitative studies, protocols and commentaries. We also excluded quantitative studies without a valid counterfactual, such as single group pre-post designs, uncontrolled non-equivalent control group designs, descriptive cross-sectional analyses, and cohort or case-control studies that did not adjust for confounding using selection-on-observables or design-based identification methods.

Search strategy

Reviewing systematic reviews

To identify eligible studies, we adopted a pragmatic search strategy that leveraged the work of recent high-quality reviews in this field. Specifically, we drew on:

- a systematic review by Puerto et al. (2022), which covers studies published between 1990 and 2022;
- the evidence and gap map by Apunyo et al. (2022), covering studies from 2000 and updated through to October 2023; and
- an earlier review by Kluve et al. (2017), which spans the period from 1990 to 2015.

Collectively, these sources provide a comprehensive coverage of the literature on ALMPs published between 1990 and October 2023. We reviewed these reviews in detail and screened all of the studies they had identified against our own eligibility criteria.

Supplementary searches

To identify additional grey literature, we undertook screening and hand-searching of reports published on the websites of institutions and repositories known to conduct, fund, and synthesise research on this topic. The list of sources reviewed, along with the specific methods employed, are detailed in Table 17.

Table 17 Supplementary literature sources and process

SOURCE	FILTERS APPLIED	PROCESS	DATE
Clearinghouse for Labor Evaluation and Research	Causal Impact Analysis	Reviewed all records in the following topics: Entrepreneurship and Self-Employment; Job Search Assistance; Justice-Involved Youth; Opportunities for Youth; Registered Apprenticeship and Work-Based Learning; Low Income Adults; Disability Employment Policy	13/05/2025
UK Department of Work and Pensions: Employment Data Lab	—	Reviewed all records	20/05/2025
UK Cabinet Office Evaluation Registry	*Evaluation type:* Impact Evaluation *Evaluation stages:* Complete *Evaluation methods:* Bayesian Updating; Difference-in-Difference; Instrumental Variables; Interrupted Time Series Analysis; Matching; Quasi-Experimental Method; Randomised Controlled Trial (RCT); Randomised Encouragement Design; Regression Discontinuity; Synthetic Control"	Reviewed all records	20/05/2025
Institute of Labor Economics (IZA) Discussion Papers	RePEc:iza:izadps (IZA Discussion Papers, Institute of Labor Economics (IZA))	Reviewed all records returned using the search string: (youth OR young) AND ((job AND (placement OR search OR assistance OR preparation)) OR (skills AND (basic OR soft OR business OR behavio* OR technical OR vocational)) OR (training AND (skills OR technical OR vocational OR business)) OR (work AND (experience OR placement OR temp*)) OR (business AND (skills OR mentor* OR advisory)) OR (wage AND subsid*) OR (support AND (start* OR financial OR entrepreneur*)) OR (employment AND (subsidised OR subsidized OR coach* OR counsel*)) OR "self-employ*" OR "financial assistance" OR "public works" OR internship OR ALMP OR "active labour market" OR "active labor market")	20/05/2025

SOURCE	FILTERS APPLIED	PROCESS	DATE
Organisation for Economic Co-operation and Development	Topic: "Employment", "Education and skills", "Industry, business and entrepreneurship"; Language: "English"; Publication type: "Report", "Working paper", "Policy paper", "Paper series"	Reviewed all records returned using the search term: "evaluation"	16/05/2025
Pathways to Work Evidence Clearinghouse	Selected populations: Young adults (aged 16-24)	Reviewed all records	13/05/2025
United States Administration for Children and Families, Office of Planning, Research and Evaluation	—	Reviewed all records listed under: "Youth Services" and "Self-Sufficiency, Welfare & Employment"	21/05/2025
VOCEDplus	—	Reviewed all records returned using the search string: ((all_subject:Youth OR tm_metadata.abstract:Youth OR tm_metadata.abstract:Young) AND (all_subject:"Program evaluation")) AND ((all_subject:Traineeship OR all_subject:"Work experience" OR all_subject:"Workforce development" OR tm_metadata.abstract:internship) OR (tm_metadata.abstract:training AND (tm_metadata.abstract:skills OR tm_metadata.abstract:technical OR tm_metadata.abstract:vocational OR tm_metadata.abstract:business)) OR (all_subject:mentoring OR tm_metadata.abstract:mentoring OR tm_metadata.abstract:mentor) OR (all_subject:"Entry level training" OR (tm_metadata.abstract:skills AND (tm_metadata.abstract:soft OR tm_metadata.abstract:basic OR tm_metadata.abstract:business OR tm_metadata.abstract:technical))) OR (all_subject:Subsidy OR tm_metadata.abstract:subsid*) OR (all_subject:"Job searching" OR (tm_metadata.abstract:job AND (tm_metadata.abstract:placement OR tm_metadata.abstract:search OR tm_metadata.abstract:assistance OR tm_metadata.abstract:preparation))) OR (tm_metadata.abstract:"public works") OR (tm_metadata.abstract:"financial assistance") OR (all_subject:"Labour Market Program" OR tm_metadata.abstract:ALMP OR tm_metadata.abstract:"active labour market" OR tm_metadata.abstract:"active labor market"))	21/05/2025

Study selection

Record identification and deduplication

Studies included in the Puerto et al. (2022) and Kluve et al. (2017) review were manually entered into Zotero and exported as *.bib* files, while a *.RIS* file of included studies was directly exported from the Apunyo et al. (2022) EGM. Each reference list was then uploaded separately to Covidence for automated de-duplication, with additional duplicates flagged manually during the screening process.

Title and full-text screening

Study records were screened for relevance to the review aims and excluded if they did not meet eligibility criteria for setting, population, study design, intervention, outcome, or comparator.[4] Screening was conducted in two stages by human reviewers only (no AI assistance): (a) title and abstract screening, and (b) full-text review. At both stages, a minimum of two blinded reviewers worked independently without access to one another's inclusion or exclusion decisions. Conflicts arising at the title and abstract stage were resolved by a third reviewer; for full-text screening, disagreements were discussed within the review team (via Slack), with final decisions facilitated by a third reviewer.

Data extraction

Each included report was assigned a unique identifier in the form of a BibTeX key generated in Zotero. Full-text papers and supplementary materials were stored in a dedicated Dropbox folder, organised at the study level, with one folder created per study to ensure systematic record-keeping and ease of access across the review team.

Data were extracted into a structured template developed specifically for this review and hosted on Google Sheets to enable collaboration. The template contained separate sheets for: (a) study-level information (e.g., metadata, study design, population characteristics, intervention funding), (b) intervention and comparison components, and (c) individual outcomes, including the quantitative data required for effect-size

[4] A hierarchy for study exclusion was developed and included in the screener instructions, it is available on OSF as part of the review registration (Taylor *et al.*, 2024).

transformation. Detailed instructions and a companion data-extraction checklist were provided to all reviewers to ensure consistency in how each item was coded. [5]

Data extraction was conducted in stages. First, all reviewers were trained on the use of the template, and five pilot studies were extracted to validate and refine the tool. During primary extraction, a single reviewer extracted all information for each study. Secondary extraction involved a second reviewer independently checking the accuracy of the primary extraction. Any discrepancies were flagged directly in Google Sheets and resolved through discussion within the team (via Slack), with arbitration by a third reviewer where required. All data extraction was undertaken by human reviewers, without AI assistance.

Risk of bias in included studies

Confidence in the internal validity of included studies was assessed using the revised JBI critical appraisal tools developed by Barker and colleagues. For studies using selection-on-observables and design-based identification approaches, we applied the 9-item checklist for quasi-experimental designs (Barker *et al.*, 2024). For randomised controlled trials, we applied the 13-item checklist for RCTs (Barker *et al.*, 2023). These tools examine common sources of bias across domains including temporal precedence, selection and allocation, confounding, intervention delivery, outcome measurement, participant retention, and statistical conclusion validity. Each item was coded as Yes, No, Unclear, or Not Applicable. Risk of bias (ROB) assessment was conducted concurrently with data extraction: one reviewer undertook the initial assessment, and a second reviewer independently checked it. Discrepancies were flagged in Google Sheets and resolved through discussion within the team (via Slack), with a third reviewer acting as a tiebreaker. All assessments were undertaken by human reviewers, without AI assistance.

Both appraisal tools allow users flexibility in how results are summarised. We considered this flexibility essential, as many tools flag policy and social intervention studies as "high risk" despite their methodological appropriateness for the field. Our interest lay in within-domain variation across studies, rather than in judging each study against an idealised design. To that end, we applied clear decision rules across designs: (a) the presence of a clear bias in any single domain resulted in a classification of high ROB; (b) three or more items scored as Unclear also led to a high ROB; and (c) studies that did not meet either threshold were classified as of acceptable ROB (i.e., not-high ROB).

[5] A copy of the data extraction template, instructions and checklist are all available on OSF as part of the review registration (Taylor *et al.*, 2024).

We also made context-specific adaptations to each tool. In the quasi-experimental checklist, we disregarded the item requiring pre- and post-intervention outcome measurement[6], as nearly all studies relied on administrative data collected only at follow-up. In the RCT checklist, we excluded the two items concerning participant[7] and provider[8] blinding, which are infeasible in the context of ALMPs, and the item concerning analysis by randomised group[9], since we planned to include intention-to-treat in our modelling. These adaptations ensured that our quality appraisal remained both rigorous and relevant to the evaluation of ALMP interventions.

Outcome classification taxonomy

Outcomes of interest to this review were measured and reported in a wide variety of forms. To ensure that we pooled like with like, we developed a post hoc taxonomy that grouped outcomes into comparable constructs (Table 18). Within the employment and education-related measures that this review focuses on, we classified outcomes into seven domains:

1. **Labour Force Status** — Indicators of an individual's employment status, measured as current, recent (up to ≤12 months recall) status, or "ever since baseline".
2. **Employment Compensation** — Monetary returns conditional on being employed, including wages, salary, and cumulative pay.
3. **Employment Duration** — Cumulative time spent in employment during the follow-up window.
4. **Hours Worked** — Indicators of employment intensity, measured weekly or monthly.
5. **Total Income** — Broad measures of resources available to individuals or households, combining labour and non-labour sources e.g., earnings and transfers.
6. **Labour Market Transitions** — Measures of flows into or out of labour force states, such as entries to employment, exits from unemployment or not in the labour force.
7. **Education and Skills** — Measures of human capital accumulation, including enrolment, participation, and completion by ISCED levels; apprenticeship

[6] "Were there multiple measurements of the outcome, both pre and post intervention/exposure?"
[7] "Were participants blind to treatment assignment?"
[8] "Were those delivering the treatment blind to treatment assignment?"
[9] "Were participants analysed in the groups to which they are randomised?"

participation and completion; and acquisition of credentials or occupational licences.

Table 18 Outcome taxonomy x outcome domain

DOMAIN	OUTCOMES	VARIATION
Labour Force Status	Employed Unemployed Self-Employed Not in the Labour Force Not in Education or Training (NEET) In Employment, Education or Training (EET)	Current Recent (i.e., in last 12 months) Since baseline
Employment Compensation	Wages Labour Earnings	—
Employment Duration	Period Employed Period Unemployed (including looking for work) Period Not in the Labour Force Period EET	—
Hours Worked	Hours Worked	—
Total Income	Total individual income Household income	—
Labour Market Transitions	Unemployment Employment Not in the Labour Force	Entries Exits
Education and Skills	Foundation skills (ISCED 1) Lower secondary school (ISCED 2) Secondary school or equivalent (ISCED 3) Post-secondary non-tertiary (ISCED 4) Short-cycle tertiary (ISCED 5) Bachelor's or equivalent (ISCED 6) Master's or equivalent (ISCED 7) Doctorate or equivalent (ISCED 8) Apprenticeship participation Apprenticeship completion Occupational licence obtained	Application Participation Completion

Data preparation

Our synthesis approach was designed to maximise the number of studies that we could include in our analysis while minimising any bias that it introduced.

Effect size transformations

Our goal was to include as many eligible studies as possible while keeping all effects on a common, comparable scale. To do this, we converted all reported results to a standardised mean difference (SMD), which we believe is a reasonable choice when studies report results in different ways[10] (Borenstein *et al.*, 2009). We also applied Hedges' small-sample correction.

Every effect size was expressed as Hedges' *g* with its standard error (SE). This allowed us to synthesise continuous outcomes (e.g., earnings), binary outcomes (e.g., currently employed/unemployed), and treatment effects on a single metric. Positive values were set to reflect an improvement on the outcome (e.g., currently employed, earnings). For negative outcomes (e.g., currently unemployed), we flipped signs before analysis and flipped them back when reporting for clarity.

All transformations were implemented in R using custom functions based on Wilson's (no date) effect size calculator. Specifically:

- **Percentages or proportions** — for studies reporting arm-level proportions, percentages or odds ratios, we converted the log-odds ratio to *g* using cox logit mapping and applied the small sample correction.
- **Treatment effect** — where studies reported a mean or risk difference (typically as an average treatment effect on the treated) we converted it to *g* using a pooled SD. When a pooled SD was not reported, we derived one from the reported SE of the treatment effect under the equal-variance assumption and applied the small sample correction.
- **Means and SDs** — we combined group-level SDs into a single pooled SD, calculated the SMD from group means, and then applied the small-sample correction.

[10] Binary outcomes are typically analysed on the log-odds scale, but the majority of studies did not report the inputs needed to transform reported binary results into an odds ratios. Using Hedges' *g* let us include all studies on a single scale. Where ORs were reported, we still used them—by transforming them to an SMD—so those studies were still included.

- **Means with SEs or *t*-values** — when only SE or a two-sample t statistic were reported alongside group means, we reconstructed the underlying SDs from these values (using the sample sizes as weights), and then proceeded as above to calculate the SMD and applied the small-sample correction.
- **Chi-squared statistics** — we converted the chi-squared statistic (with one degree of freedom) into an equivalent *t*-value and then used this to recover the SMD and applied the small-sample correction.

Additional transformations of effect sizes

Several studies did not report a population treatment effect, instead they reported the same contrast split across subgroups (e.g., by sex, age or location). To avoid double-counting, we created one estimate per study x outcome x follow-up by taking an inverse-variance weighted average of the subgroup effects. This kept the study's overall contribution proportional to the precision of its components. Alongside the pooled effect, we also aggregated sample sizes and carried forward study descriptors (e.g. computing a treatment-n-weighted female proportion and averaging ages with sample-size weights).

Missing data

As with all evidence syntheses, missing or incomplete reporting posed a challenge. We sought to minimise the risk of missing data while working within the constraints imposed by the time and resources available to us. Our primary strategy was to contact study authors, where feasible, to request additional information. However, given project timelines, it was not possible to follow up with authors of all studies reporting incomplete data. As a secondary approach, when results were reported only in graphical form, we extracted numerical estimates using plot digitisation tools (Lajeunesse, 2021). Finally, where information such as sample sizes were not explicitly reported, we applied reasonable assumptions based on study design—for example, assuming a 1:1 treatment/comparison split when a study used nearest-neighbour matching. We kept a record of all assumptions made during the data transformation phase.

Inclusion in model

For each study, a single effect size was included for each outcome. Outcomes were only included if they exactly matched the taxonomy (Table 18). Where outcomes were reported at multiple follow-up time points, we selected the estimate closest to 24 months from baseline. This ensured that each study contributed at most one effect size per outcome to the model.

To ensure model stability, outcomes reported fewer than four times across studies were excluded. Including extremely sparse outcomes risks convergence problems while contributing little to cross-study borrowing of strength, and estimates would be overly sensitive to priors or single-study effects.[11]

Quantitative synthesis

Network meta-analysis

Network meta-analysis is a statistical approach that extends conventional pairwise meta-analysis by enabling the simultaneous comparison of three or more interventions that target similar outcomes in comparable populations (Tsokani, Seitidis and Mavridis, 2022). NMA combines evidence from studies that directly compare interventions with evidence obtained indirectly through common comparators, allowing relative impacts to be estimated even when some interventions have not been evaluated head-to-head. By integrating direct and indirect evidence within a single analytic framework, NMA can increase precision relative to isolated comparisons by drawing on evidence from a broader class of related interventions through indirect comparisons, and supports estimation and ranking of relative impacts across all interventions included in the evidence network (Dias *et al.*, 2018; Chaimani *et al.*, 2022).

The validity of NMA relies on the assumption of transitivity, which requires that the sets of studies being compared are, on average, similar in all key characteristics that could influence the relative impacts of the interventions (Salanti, 2012). When transitivity holds, direct and indirect evidence should be coherent, meaning that they lead to consistent estimates of the same underlying treatment contrasts. Incoherence (or inconsistency) arises when direct and indirect sources of evidence disagree beyond what would be expected by chance, signalling potential violations of the assumptions underpinning the network (Dias *et al.*, 2018; Chaimani *et al.*, 2022).

Component network meta-analysis (CNMA) extends NMA to settings where interventions are composed of multiple distinct components delivered in combination (Welton *et al.*,

[11] The excluded outcomes were: Apprenticeship duration; Bachelors or equivalent (ISCED 6) application; EET since baseline; Entries to not in the labour force; Not in the labour force since baseline; Post-secondary non-tertiary (ISCED 4) application; Quarters employed; Re-employment probability; Recent EET; Recent unemployment; Short-cycle tertiary (ISCED 5) application; Unemployed since baseline (each observed once); Masters or equivalent (ISCED 7) completion; Foundation skills (ISCED 1) completion; Lower secondary school (ISCED 2) completion; Currently employed permanently; Period not in the labour force (each observed twice); Currently employed temporarily (observed three times); and Currently EET and Period unemployed (each observed four times).

2009; Rücker, Petropoulou and Schwarzer, 2020). In many policy domains, interventions are not implemented as single, standardised treatments but as bundles of activities that vary in their configuration across settings, making it difficult to infer which elements are responsible for observed impacts. Rather than treating each intervention package as a single, indivisible unit, CNMA decomposes interventions into their constituent elements and estimates the incremental impact of each component. This approach has been applied in areas such as psychological therapies, where interventions often share overlapping components (Pompoli *et al.*, 2018; Furukawa *et al.*, 2021). Under the additivity assumption, the overall impact of a multi-component intervention is expressed as the sum of the impacts of its individual components. CNMA therefore enables identification of which components drive observed impacts and facilitates comparison across programmes that differ in their configuration, even when no two interventions are identical.

As with pairwise and network meta-analysis, heterogeneity in CNMA refers to unexplained variability in impacts across studies beyond sampling error. This heterogeneity reflects genuine differences in intervention implementation, populations, contexts, and study design, and captures the extent to which impacts vary across settings rather than uncertainty or study quality per se.

We estimated incremental component-level effects using a multivariate hierarchical Bayesian component network meta-analysis. Our model builds on methodological work on component-based evidence synthesis (Welton *et al.*, 2009) and extends it to accommodate multiple outcome domains, study designs, and ROB within a hierarchical Bayesian framework. We implemented this approach using a bespoke model developed using the *brms* R package (Bürkner, 2017).

Component effects

In our model, each intervention arm is represented as a bundle of ALMP components, and study-reported contrasts are decomposed into the sum of their component differences. This is achieved through a component–contrast coding matrix, where each component is coded as +1 if it is present in the intervention but not the comparator, −1 if it is removed relative to the comparator, and 0 if it is unchanged. For studies comparing an intervention to services as usual, this simplifies to a presence/absence coding.

The model relies on the additivity assumption that the overall intervention effect can be expressed as the sum of the incremental contributions of its constituent components. It estimates the average incremental contribution of each component by pooling information across all studies where that component appears, regardless of what other components it is delivered alongside. It allows borrowing of strength to occur within

component–outcome pairs: for example, every study that includes job search assistance and reports on employment outcomes contributes to the pooled estimate of that component's effect on employment. However, there is no pooling across different outcome domains, so the estimated effect of job search assistance on employment is distinct from its estimated effect on earnings or education. At the same time, within each outcome–component cell, the Bayesian hierarchical structure allows partial pooling across studies and designs: individual study estimates inform the group-level effect but are shrunk back toward the shared mean, particularly when based on limited or noisy data. This is particularly helpful as it guards against over-interpreting extreme or idiosyncratic findings.

We specified weakly informative Normal(0, 0.30) priors for outcome x component effects. These priors reflect prior knowledge that effects of ALMPs on standardised outcomes are typically small to modest (Card, Kluve and Weber, 2010, 2018; Kluve *et al.*, 2017; Puerto *et al.*, 2022). They also provide regularisation in a high-dimensional model, helping to stabilise estimation while still allowing the data to meaningfully update prior beliefs, and avoiding over-interpretation of sparse or noisy results.

Heterogeneity

The model incorporates between-study heterogeneity through random effects, but in a more granular way than a standard random-effects meta-analysis. Instead of assuming a single common heterogeneity term across all included studies, we estimated separate heterogeneity parameters for each component within each study design—randomised experiments (RE), selection on observables (SOO), and design-based identification (DBI). This approach allows both the type of component and the study design to inform how much variation is expected between studies. For example, the impact of wage subsidies may vary more widely across studies than the impact of employment counselling, and this variation may itself be greater in SOO or DBI studies than in REs. By structuring heterogeneity in this way, the model avoids forcing all components and designs into a shared variance structure and instead allows heterogeneity to be estimated where it arises. In this context, the heterogeneity parameter (τ) can be interpreted as the standard deviation of the underlying true effects across studies for a given component and design, with larger values indicating greater unexplained variability in effects across settings rather than greater uncertainty or lower study quality. For example, a τ of 0.10 for a given component within a specific study design implies that, across studies using that design, roughly two-thirds of the underlying true effects would be expected to lie within ±0.10 effect size units (*g*) of the average effect for that component.

Priors on these heterogeneity parameters were weakly informative Student-t (3, 0, 0.25) distributions on the standard deviations, applied at the component x design level. In the

brms package which we used for our analysis k, these priors are implicitly truncated at zero, and therefore correspond to half-Student-t priors on the heterogeneity standard deviations. These priors regularise extreme estimates while still permitting substantial variability when indicated by the study results.

Study design and quality

Combining evidence from randomised and non-randomised studies is sometimes necessary—particularly when randomised evidence is sparse—and often contentious in evidence synthesis (Efthimiou *et al.*, 2017; Hussein *et al.*, 2023; Reeves *et al.*, 2024). Different methods have been proposed, ranging from the extremes of assuming exchangeability and pooling all evidence together, or excluding non-randomised evidence altogether. More nuanced approaches include down-weighting non-randomised evidence based on ROB assessments, incorporating explicit bias adjustment parameters, using non-randomised evidence to inform priors or using hierarchical models that account for study design differences.

In this review, non-randomised studies accounted for more than half of the eligible evidence, making it important to include them in the synthesis in a careful and principled way. Following Efthimiou et al. (2017), we incorporated study design directly into the model's hierarchical structure. REs were taken as the reference category, while studies using selection-on-observables (SOO) or design-based identification (DBI) methods were assigned explicit mean-shift parameters to capture potential systematic differences relative to REs. In practice, these parameters allow the model to estimate whether, on average, effects reported in SOO or DBI studies differ systematically from those in REs. This does not automatically penalise non-randomised evidence, but it does prevent it from being assumed equivalent to that from REs. If the data suggest a bias, the model will estimate and adjust for it; if not, the shift remains close to zero under the weakly informative priors.

Risk of bias was handled in a parallel but distinct way. Following Verde (2021) we modelled potential bias explicitly. From the JBI quality assessment tools, each study was coded as either 'high ROB' or 'acceptable ROB'. The model included a main effect for high ROB (assuming acceptable ROB as baseline), plus interactions between ROB and study design type. This meant that any systematic bias associated with higher-ROB evidence was not imposed uniformly but was estimated separately within study designs. For instance, an RE with a high ROB was allowed to have a different bias adjustment than a SOO study with a high ROB. Priors on these ROB and design–quality interaction terms were weakly informative Normal centred at zero (SD = 0.25–0.30), reflecting uncertainty about the presence and size of such biases while allowing the data to inform the direction and magnitude. In practice, this meant that evidence with a high ROB

could still contribute to the synthesis, but the model adjusted for possible bias in a way that was specific to the type of study design, rather than assuming a one-size-fits-all penalty.

Outcome timing

To account for variation in outcome reporting across studies, we centred follow-up duration at 24 months. We selected this reference point because it represents a common follow-up horizon in the included studies and corresponds to a period by which short-run "lock-in" effects—particularly for training-based programmes—are likely to have dissipated. This choice also facilitates comparability across heterogeneous intervention components with differing implementation durations.

For studies reporting outcomes at multiple time points, we included only the measurement closest to this 24-month reference in the model dataset. The model then estimated slopes for each outcome domain (outcome-specific) to capture how effects change when outcomes are measured earlier or later. We placed weakly informative Normal(0, SD = 0.10) priors on these slopes, reflecting the expectation that effects are unlikely to change radically with a small shift in measurement timing. This specification means that all component effects are interpreted as being estimated at 24 months post-baseline, providing a common anchor point for comparison. An added advantage is that it allowed us to retain studies with different follow-up intervals, rather than discarding them.

Subgroup analysis

To explore potential effect modification, the model included interaction terms between intervention components and study-level covariates (sex composition and mean age), enabling estimation of component effects across different population subgroups. Compared with the broader model, priors for these subgroup interactions were specified to be more concentrated around zero (e.g., SD = 0.05–0.10). This reflects an a priori expectation that moderation effects, if present, are likely to be modest in magnitude, and serves to regularise a large number of interaction parameters, reducing the risk of overinterpretation of chance subgroup patterns arising from sparse data.

Subgroup analysis by sex

Subgroup effects by sex[12] were incorporated into the model by including interaction terms between each intervention component and the centred proportion of female participants in the study sample. This specification allowed us to estimate how the average treatment effect of each component changed as the proportion of females varied between studies, while keeping the component's main effect outcome-specific. To calculate subgroup contrasts, we predicted component effects with the female proportion set to 0 (all-male sample) and to 1 (all-female sample) on the centred scale, and then took the difference between these predicted values. The resulting contrasts represent the estimated differential effect of a component in studies with all females compared to studies with all males.

These estimates should be interpreted cautiously. Because the unit of analysis is at the study-level, they risk the ecological fallacy—drawing conclusions about individual-level moderation from study-level associations. In practice, programmes serving all-female or all-male participants may differ in implementation, and populations may vary in ways other than sex. Thus, observed contrasts could reflect correlated study-level factors rather than true causal differences by sex. While these results do not imply causal individual-level moderation, they are nonetheless informative for highlighting potential heterogeneity of intervention effects across populations and for guiding hypotheses about which components may work differently for young men and women.

Subgroup analysis by age

Subgroup effects by age were incorporated into the model by including interaction terms between each intervention component and the centred mean study age. This specification allowed us to estimate how the average treatment effect of a component changed as the mean age of participants in the study sample increased, while keeping the main effects outcome-specific. To generate contrasts, we re-estimated component effects at a set of representative raw ages (e.g., 16, 18, 20, 22, and 24 years), converting each to the z-scored scale used in the model. These predictions can be compared across ages to show how the estimated effect of a component differs for younger versus older study populations.

As with the sex subgroup analysis, these estimates are based on between-study variation and may be confounded by other study-level factors correlated with participant age.

[12] We use the term 'sex' rather than 'gender' because this is the terminology employed in the primary studies. Where reported, studies present a binary variable without defining or measuring gender identity.

They should not be interpreted as causal evidence that an individual's age moderates treatment effects. Nevertheless, they provide a useful lens for examining potential heterogeneity of intervention effects across younger and older youth populations, and for generating hypotheses about which components may be more effective for different age groups.

Interpretation and Reporting

Interpreting Bayesian output

Our Bayesian analysis produces posterior probability distributions for each component–outcome effect. The major advantage of this framework is that it allows us to report the probability that an effect is greater than zero (Pr > 0), or that it exceeds any other chosen threshold. We believe this is an asset in knowledge translation as it communicates uncertainty in a way that is interpretable to both technical and non-technical audiences. Alongside these probabilities, we reported the posterior median as a measure of central tendency and the 95% credible interval (CrI), defined as the interval within which the true effect lies with 95% probability. In other words, if the 95% CrI for an outcome x component effect is [0.05, 0.30], then there is a 95% probability that the true effect lies between those two values.

Interpreting the size of the effect

To avoid over-interpreting results close to zero we specified a region of practical equivalence (ROPE), an interval around zero within which effect sizes are considered too small to be of practical importance (Kruschke and Liddell, 2018), where $|g| < 0.05$. This boundary reflects a substantive judgement about the magnitude of effect that should be treated as negligible. We report both the probability that the posterior lies within the ROPE (i.e., little or no effect) and the probability that it exceeds this threshold $Pr(|g| > 0.05)$. To aid interpretation, we report the posterior probability of a 'meaningful' effect $|g| > 0.05$ versus an effect that is 'practically equivalent' (we also use the term 'little or no effect'). These probabilities correspond to the proportion of the posterior distribution falling outside or within the ROPE, respectively.

To aid interpretation across component x outcome effects, we applied thresholds that classify effects into four groups: little or no effect, low impact, medium impact, and high impact (Table 19). These thresholds are based on those used in the first edition of the Toolkit and in our earlier report (Taylor *et al.*, 2023), and they allow us to summarise the proportion of the posterior distribution falling within each impact level.

Table 19 Thresholds for effect size magnitude

CATEGORY	EFFECT SIZE THRESHOLD
Little or no effect	$\|g\| < 0.05$
Low impact	$0.05 \leq \|g\| \leq 0.10$
Medium impact	$0.10 < \|g\| \leq 0.20$
High impact	$\|g\| > 0.20$

Reporting filters

We applied two reporting filters.[13] First, to avoid presenting results that were indistinguishable from our prior assumptions, we assessed whether the posterior distribution had been substantially updated by the data. This was evaluated using two complementary diagnostics: (i) the Kullback–Leibler divergence (KLD), which quantifies how far the posterior deviates from the prior distribution, and (ii) the prior–posterior overlap (PPO), which measures the degree of similarity between prior and posterior densities. Results were retained for reporting where PPO ≤ 0.60 or KLD ≥ 0.10, indicating meaningful updating of the prior by the data. Results failing to meet either criterion (i.e., high PPO and low KLD) were suppressed to avoid overstating evidence.

Second, for clarity and parsimony, we excluded two outcome domains from reporting altogether. Specifically, we did not present results for labour market transitions or total income outcomes, both of which were included in the network primarily to strengthen linkages across studies. As these outcomes were of secondary interest and not central to our research questions, they were omitted from the main reporting.

Software

The software we used in this review is detailed in Table 20.

Table 20 Software details

NAME	PURPOSE	CITATION
Covidence	Screening and de-duplication	Veritas Health Information (no date)

[13] Fully non-informative priors were explored but proved infeasible in this setting. Given the high-dimensional nature of the model, substantially weaker priors led to weakly identified posteriors and unstable estimation.

NAME	PURPOSE	CITATION
Google Sheets	Record data extraction and risk of bias assessment	Google (2024)
R Project for Statistical Computing	Quantitative analysis (using *brms*) and visualisation (using *ggplot2*) — including effect size transformation and meta-analysis. The *juicr* package was used to extract data from figures.	R Core Team (2025), Burkner (2017), Wickham (2016) and Lajeunesse (2021)
Slack	Collaboration and communication	Slack Technologies (2025)
Zotero	Reference management	Corporation for Digital Scholarship (2022)

Protocol

Registration

The review followed an explicit protocol. The protocol was reviewed by YFF and its external advisors and is available on Open Science Framework at https://osf.io/dbfkr (Taylor *et al.*, 2024).

Deviations

Our OSF registration assumed that the analytic approach would closely follow Taylor et al. (2023), which relied on a frequentist CNMA framework. Consequently, many of the robustness checks, sensitivity, and subgroup analyses we proposed were designed with that framework in mind.

In practice, two factors prompted a shift from the original plan. First, the number of eligible studies was substantially greater than anticipated, and the additional time required for data extraction and ROB assessment limited the resources available for implementing the full set of planned analyses. Second, our analytic approach evolved: we implemented a Bayesian multivariate CNMA. This framework enabled us to incorporate study design and other key characteristics directly into the model structure, rendering several pre-specified sensitivity analyses redundant (e.g., separate models by study design). Similarly, while we had planned to assess transitivity using node-splitting, we did not implement this due to time and resource constraints, with coherence assessed indirectly within the Bayesian multilevel framework.

The protocol also proposed a wide range of subgroup analyses to explore whether ALMP effects varied by study population, intervention characteristics, outcome

measurement, or analysis features, drawing on findings from earlier reviews (Kluve *et al.*, 2017; Puerto *et al.*, 2022; Taylor *et al.*, 2023). Although this plan reflected our strong interest in heterogeneity, the breadth of analyses proved too ambitious given the size of the evidence base and the project's timelines. As a result, many pre-specified subgroup analyses were not undertaken. We acknowledge these deviations from the protocol but believe our analytic choices provide a coherent and robust framework for capturing component-level impacts of ALMPs.



Results

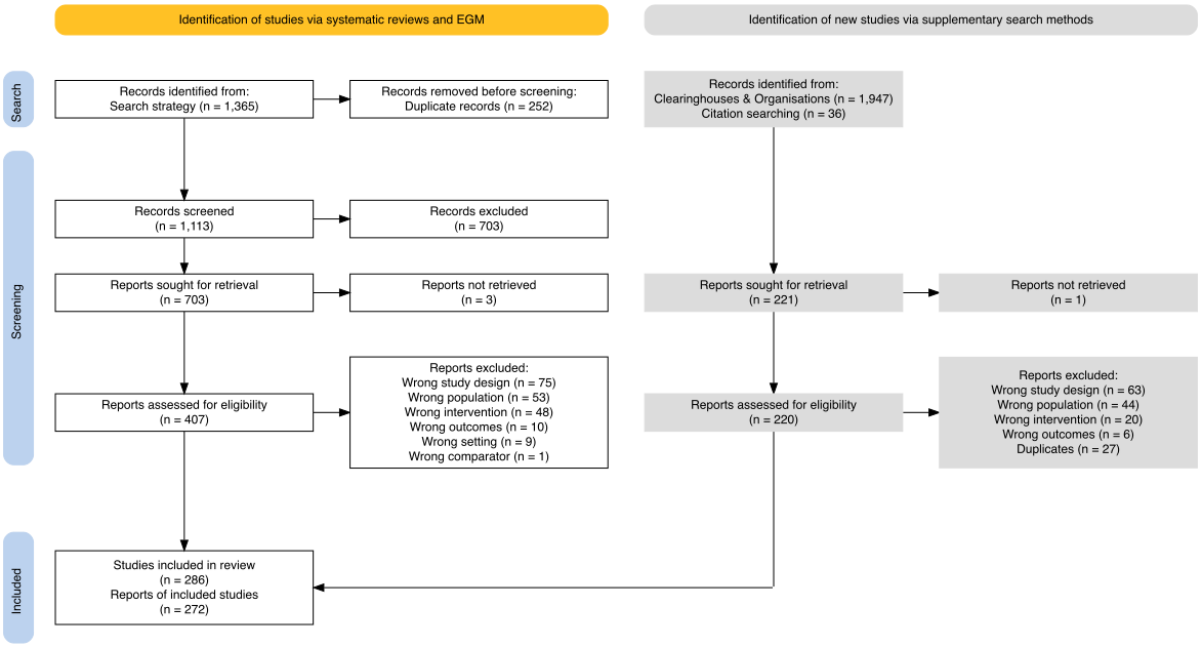
Study-level results

Included studies

Search results

The search strategy identified 1,335 records from the Puerto et al. (2022), Kluve et al. (2017), and updated Apunyo et al. (2022) reviews, of which 1,113 were unique and screened for inclusion. An additional 1,983 records were sourced from supplementary searches. Following title and abstract screening, 627 full-text reports were assessed for eligibility. Of these, 272 reports, representing 286 unique studies, met the inclusion criteria. The overall process is summarised in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flowchart (Figure 1).

Figure 1 PRISMA 2020 flowchart



Building the model dataset

Our final model drew on results from 157 unique studies. The process of moving from the full pool of eligible studies to the analytic dataset is summarised in Table 21. After screening, 286 studies were available for extraction. At this stage, 70 were deprioritised because essential information was missing, most often the variance of treatment effects. A further 9 studies were removed during data cleaning because their outcomes were

out of scope for this model. In line with our extraction protocol, we had initially treated subgroup analyses reported within the same study (e.g., results stratified by sex or age) as distinct "studies." When converting reported results to a common effect size, these stratified results were subsequently pooled, reducing the effective study count by 49. Finally, in preparing the model, we excluded one study that reported outcomes appearing fewer than five times in the network, yielding a final set of 157 studies for analysis.

Table 21 Getting to our model data

STAGE	FILTER	# STUDIES	TOTAL # STUDIES
Screening	—	—	286
Data extraction	Exclude studies with missing data	-70	216
Data cleaning	Exclude studies with outcomes out of scope for this iteration of the model[14]	-9	207
Effect size transformation	Pool studies reporting results stratified by demographic characteristics	-49	158
Model calibration	Exclude studies reporting outcomes appearing < 5 times in the network	-1	157

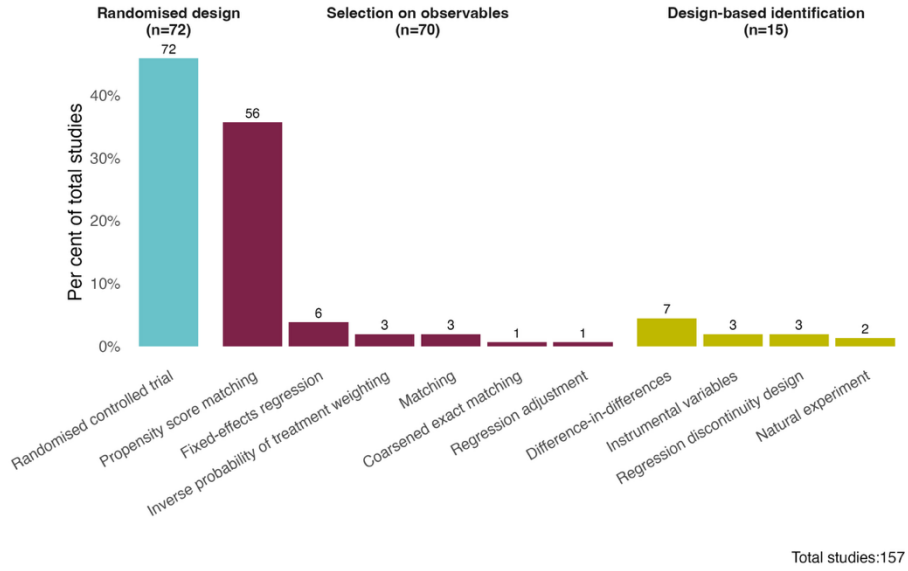
Characteristics of included studies

Study design

Figure 2 shows the distribution of study designs across studies included in our model data. Almost half (46 per cent) of the studies were randomised controlled trials (n=72). Among the non-randomised studies, most relied on selection-on-observables methods (n=70) with propensity score matching (n=56) being the most common. A smaller proportion (~10 per cent) employed design-based identification strategies such as difference-in-differences.

[14] Studies that only reported outcomes in the following domains were excluded from the network for this iteration of the model: Capability-enhancing assets, Employment Quality, Social Networks and Relationships, Job Seeking Behaviour, Criminal Justice System Involvement, Physical and Mental Health, Substance Use or Other economic outcomes.

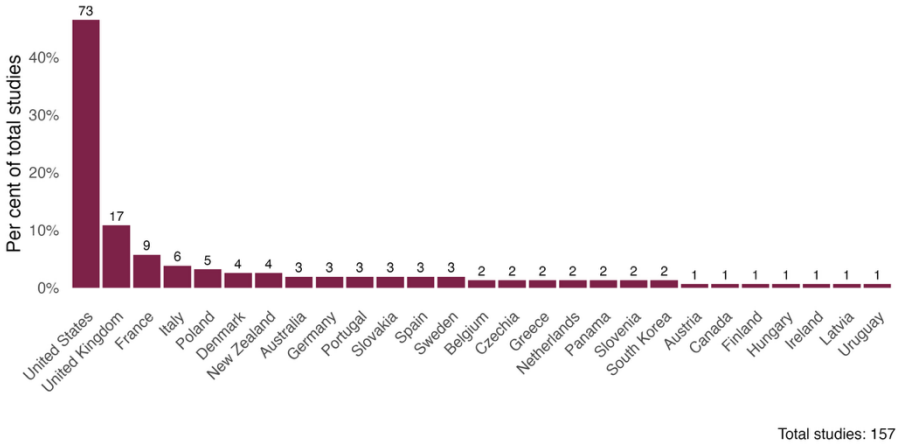
Figure 2 Distribution of study designs across studies in model data



Study location

As shown in Figure 3, almost half (46 per cent) of studies were conducted in the United States (n=72). The United Kingdom is well represented contributing ~10 per cent of the sample.

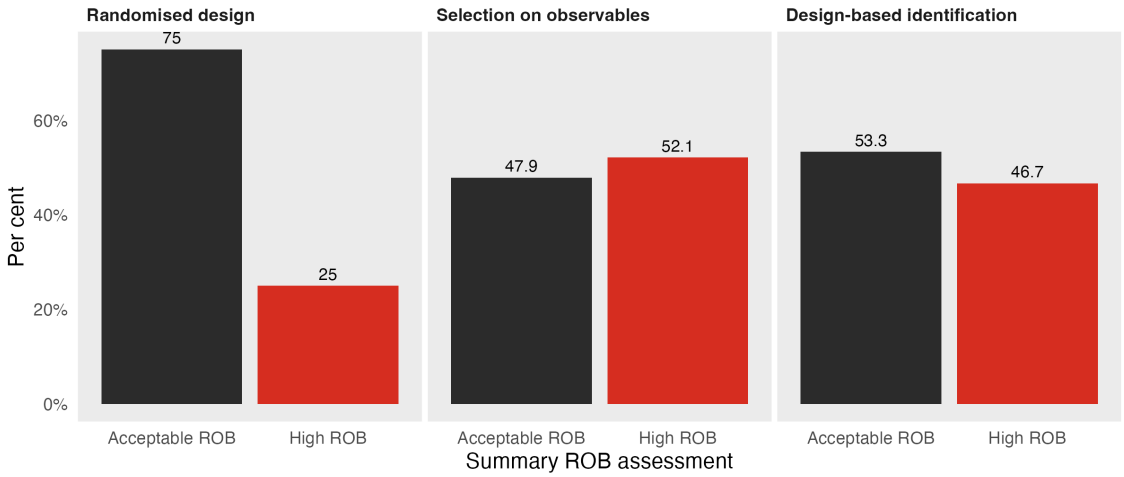
Figure 3 Distribution of locations across studies in model data



Risk of bias

We assessed risk of bias (ROB) using the updated JBI critical appraisal tools for randomised controlled trials (Barker *et al.*, 2023) and quasi-experimental studies (Barker *et al.*, 2024). Scores were summarised across domains to create a binary measure of ROB: 'high ROB' versus 'acceptable ROB' (i.e., not-low ROB) — see Methods for details. The distribution of quality assessments, stratified by study design, is shown in Figure 4. Around one-quarter of randomised studies were judged to have a high ROB. Among non-randomised designs, a majority of studies relying on selection-on-observables approaches were rated as having high ROB, whereas just under half of studies using design-based identification strategies received this rating. Detailed results by tool and question are provided in Appendix A.

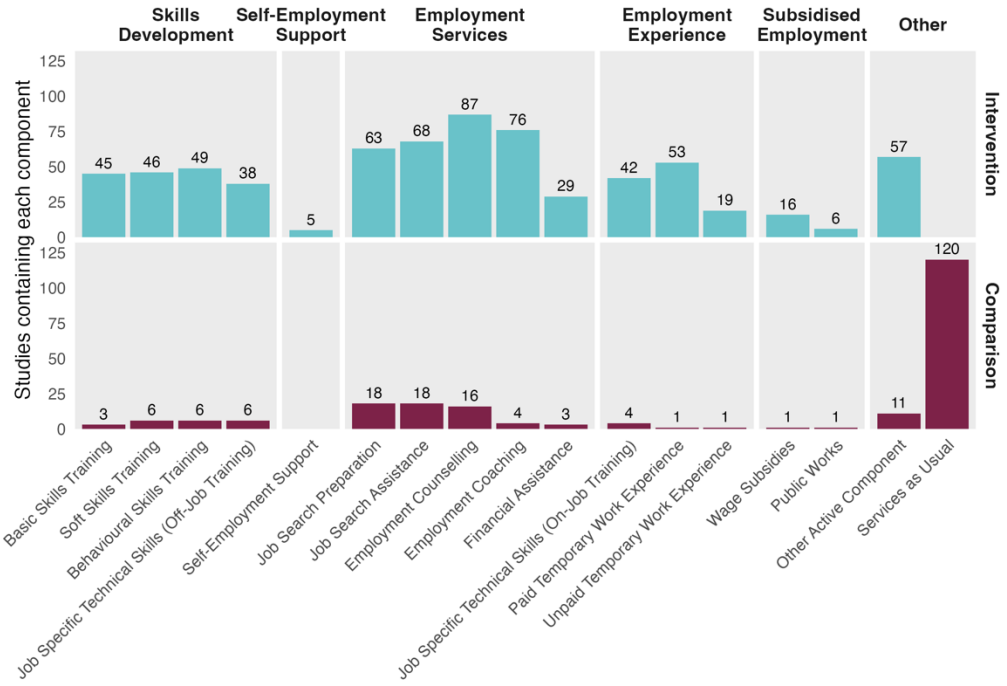
Figure 4 Distribution of risk of bias results by study design



Intervention components

The distribution of intervention components across intervention and comparison arms of studies in the analytic sample is shown in Figure 5. The most commonly evaluated components were employment services, particularly employment counselling and employment coaching. Just over one-third of studies included an "other" active component that did not align with our predefined taxonomy. More than three-quarters of study comparisons were made against services as usual. In contrast, components relating to self-employment support were rarely included. To aid model convergence, we combined business skills training (n = 2), business advisory and mentoring (n = 4), and financial and start-up support (n = 1) into the overarching self-employment support category (n = 5).

Figure 5 Distribution of components across intervention and comparison arms of studies in model data



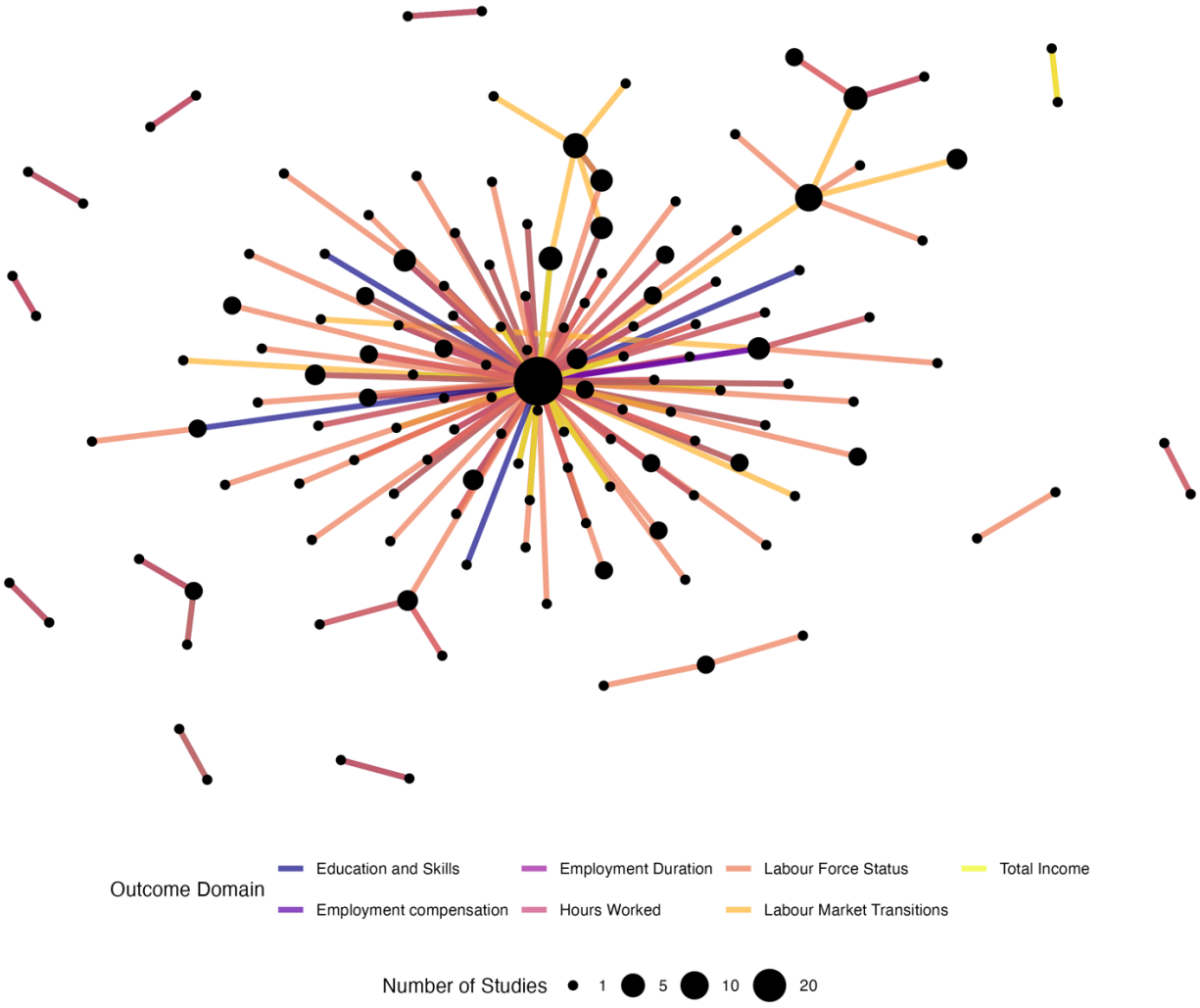
Network structure

The intervention network comprised 157 studies contributing 125 pairwise comparisons across 136 treatment components. The network was not fully connected: it consisted of 13 disconnected subnetworks, the largest of which contained 110 studies, while the remainder were small networks of 2–3 studies each. Most comparisons linked interventions through services as usual (SAU), which acted as the dominant hub in the network. The network contained two independent loops, with the shortest cycle involving job-specific off-the-job training, on-the-job training, public works, and SAU. Although the network appears moderately sparse and fragmented at the intervention level, the component-based approach helps to mitigate this limitation since information is pooled across shared components even when entire intervention packages are not directly connected.

Figure 6 depicts the network map for studies included in our analytic sample. Each node represents a component, with node size proportional to the number of studies, and edges representing direct comparisons between components within a study. Edge colours indicate the outcome domain through which the comparison was reported. Most comparisons were anchored through services as usual, which forms the central hub

of the network. Since our analysis is multivariate, the map also illustrates how links across outcome domains create additional connections, enabling the model to integrate parts of the network that would otherwise remain disconnected.

Figure 6 Network map for studies included in our model



Model estimation and diagnostics

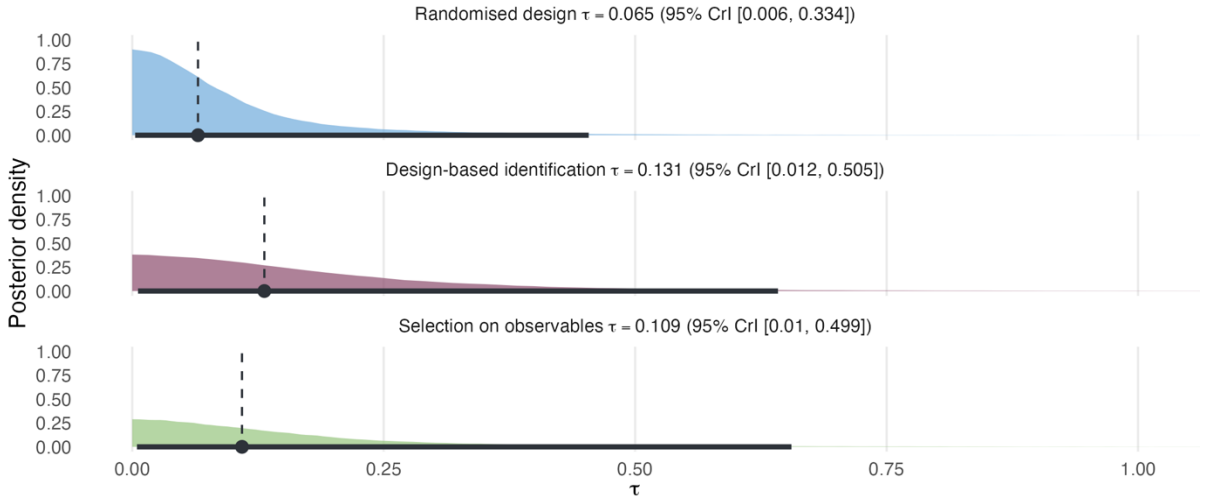
Estimation

We fit a model with 4 chains (4,000 iterations per chain; 2,000 warm-up), using a target acceptance probability of 0.99 and a maximum tree depth of 16. All chains mixed well: the Gelman–Rubin statistic (R-hat, a measure of cross-chain convergence, where values close to 1 indicate convergence) was 1.00 for all reported parameters, and bulk and tail effective sample sizes (ESS, the number of independent draws equivalent to the correlated Markov chains) were large (typically >1,500 and often >5,000). Across 8,000 post-warmup draws, only 3 transitions (<0.05%) ended with a divergence. Given the very small number of divergences and excellent R-hat/ESS values, we judged convergence to be adequate and inferences robust. Trace plots showed good chain mixing with no pathologies.

Heterogeneity

The estimates in Figure 7 reflect the global heterogeneity parameter (τ) by study design, pooling across all intervention components. For REs, τ was small (median = 0.065), while DBI and SOO studies exhibited larger values (median = 0.131 and 0.109, respectively). These study design-level τ estimates summarise the residual heterogeneity across studies, after the model accounts for observed components, outcome timing, and study-level covariates. When we present the results by component, we also present τ by study-design and the component-level, allowing us to see which components exhibit greater heterogeneity. Reporting both levels is useful: the design-level τ highlights systematic differences between estimates from RE, SOO and DBI evidence, while the component-level τ shows whether these differences are concentrated in particular components.

Figure 7 Posterior distribution of between study heterogeneity (τ) by study design



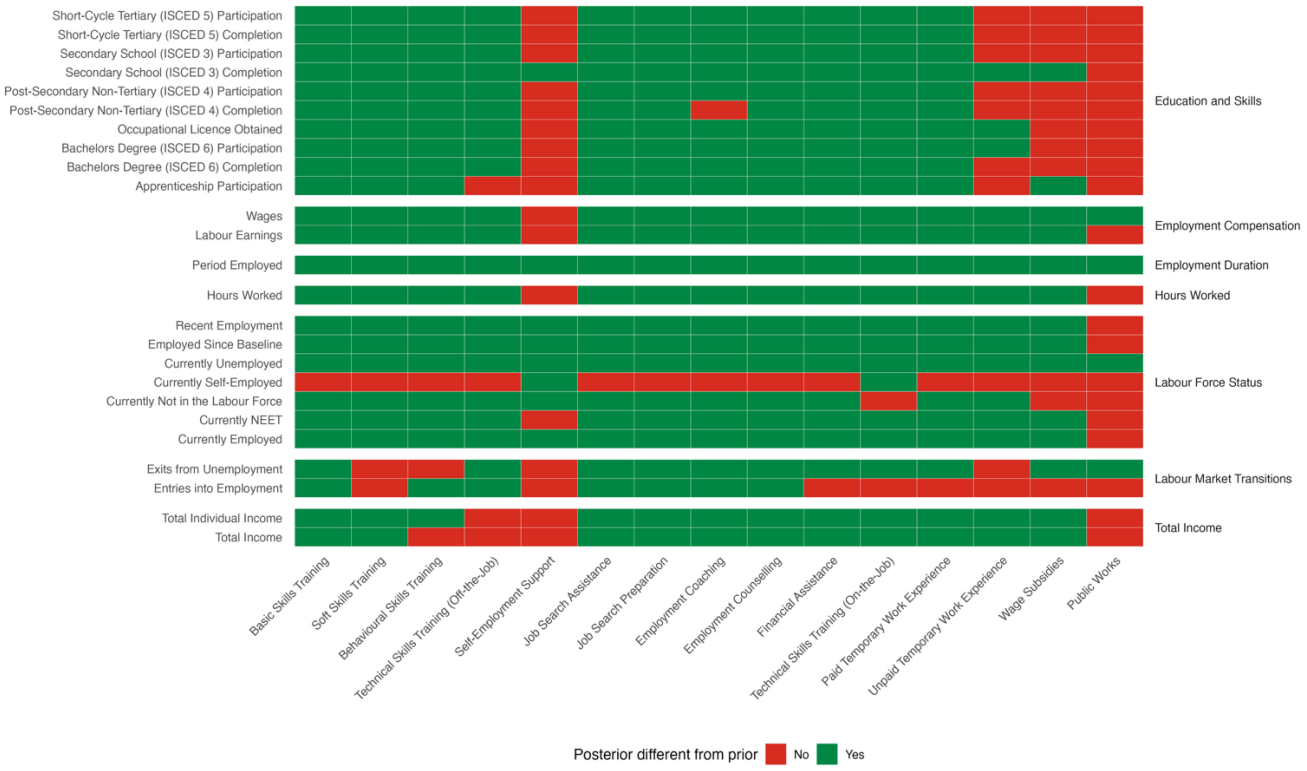
Diagnostics

Posterior predictive checks indicated a reasonable fit to the observed effect-size distribution. Full diagnostics and plots are available on request.

Outcome coverage

Figure 8 summarises the application of our reporting filters by showing, for each component x outcome combination, whether the posterior distribution was meaningfully updated relative to the prior. Green cells indicate estimates where the posterior diverged sufficiently from the prior (based on our PPO/KLD thresholds), while red cells indicate cases where the data provided little additional information beyond prior assumptions. We do not present detailed results for the latter.

Figure 8 Outcome matrix showing application of reporting filters across component x outcome combinations





Skills Development

Meta-analysis results

Basic Skills Programmes

Key findings

- **Most impacts are small and often favour SAU**. Medium- or high-impact effects are uncommon, with two exceptions: apprenticeship participation, which is likely (Pr > 0.05 = 0.75) to favour the intervention and be medium or large in size (67%), and hours worked (Pr > 0.05 = 0.55), where medium or high impacts are plausible (41%).
- **Positive labour-market effects are limited, but education pathways appear more responsive**. Improvements in apprenticeship participation and occupational licensing (Pr > 0.05 = 0.62) suggest Basic Skills Training may support longer-term labour market progression indirectly.
- **Impacts vary by population**. Effects are very likely (97%) larger in all-female study populations. There is also evidence that impacts decline as mean study age increases.
- **How to make sense of this.** The analysis focuses on the impact of basic skills training interventions, rather than the impact of attaining basic skills themselves. While Basic Skills Training has a limited impact on labour market outcomes, building this skill set arguably unlocks apprenticeship participation, and to a lesser degree, occupational licence accreditation, which longer term should have positive labour market outcomes. Basic skills provide the essential underpinnings for entry and progression in work and learning. Moreover, possessing these skills can increase individuals' confidence as well as their capability to manage literacy and numeracy demands of wider life, such as managing household budgets and bills.

Definition

Basic skills training focuses on enhancing foundational competencies such as literacy, numeracy, and digital skills that are essential for individuals to effectively engage in education, training, or employment. These programmes aim to bridge skill gaps from the compulsory education phase and equip participants with the necessary abilities to navigate personal and professional environments successfully. Basic skills training is often targeted towards individuals who may have had limited formal education.

Evidence profile

A summary of the evidence used to inform the analysis of Basic Skills Programmes is summarised in Table 7. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 22 Evidence profile for Basic Skills Training

SUMMARY	COUNT			
Number of studies	45			
Number of effect sizes	157			
Study design	RE: 24	SOO: 19	DBI: 2	
Risk of bias	Acceptable: 18		High: 27	
Study design x risk of bias	Acceptable High	RE: 19 RE: 5	SOO: 6 SOO: 13	DBI: 2 DBI: 0
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=27); Recent Employment (n=11); Currently Unemployed (n=5); Currently NEET (n=3); Currently Not in the Labour Force (n=4)			
Employment Compensation	Labour Earnings (n=11); Wages (n=5)			
Employment duration	Period Employed (n=9)			
Hours Worked	Hours Worked (n=4)			
Education & Skills	Secondary School (ISCED 3) Participation (n=1); Secondary School (ISCED 3) Completion (n=22); Bachelors Degree (ISCED 6) Participation (n=10); Bachelors Degree (ISCED 6) Completion (n=8); Short-Cycle Tertiary (ISCED 5) Participation (n=1); Short-Cycle Tertiary (ISCED 5) Completion (n=5); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=3); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=5); Apprenticeship Participation (n=1); Occupational Licence Obtained (n=6)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Basic Skills Training. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

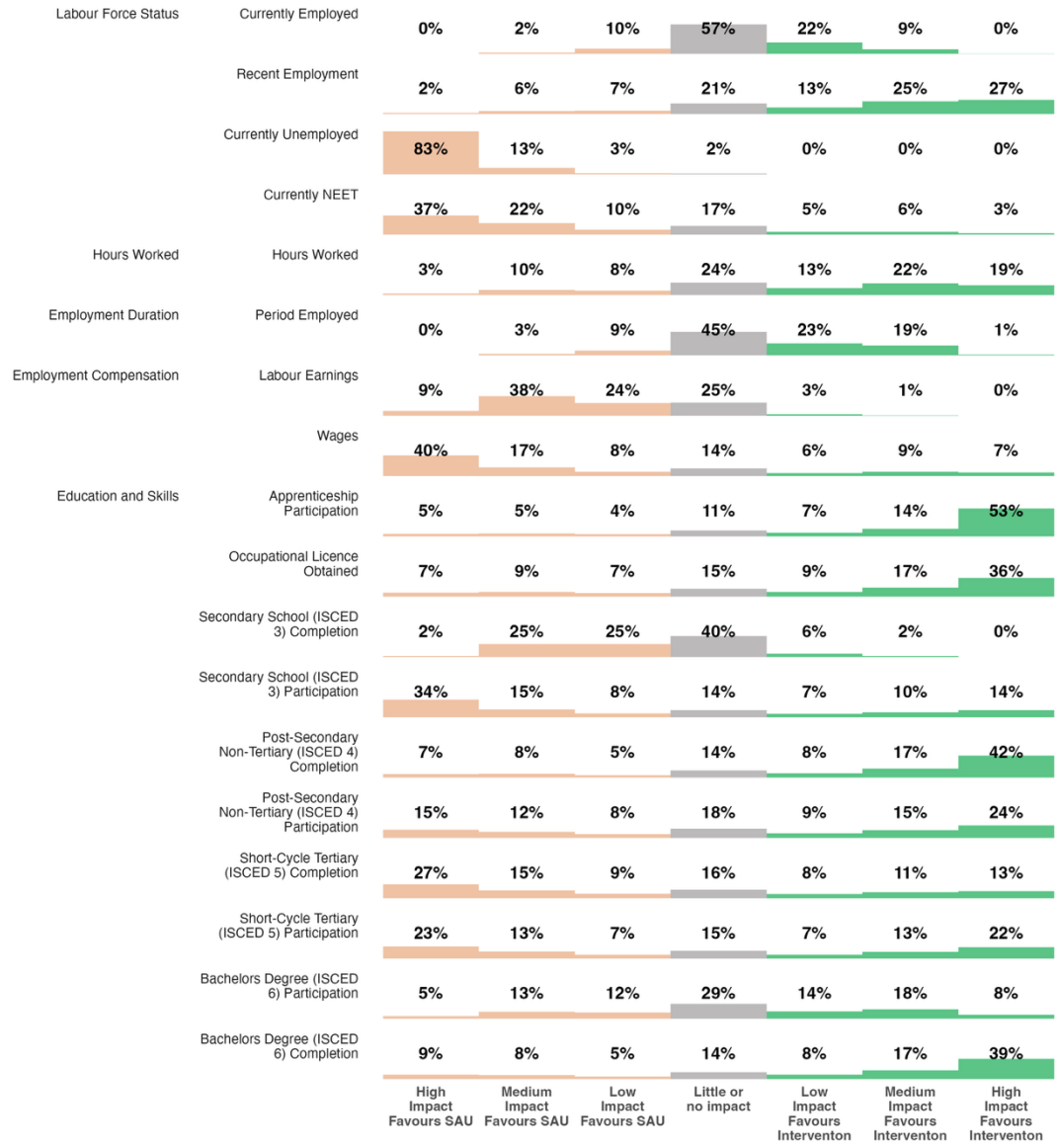
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 9 shows the posterior probability that the effect of Basic Skills Training on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 9 Probability of the scale of impact of Basic Skills Training

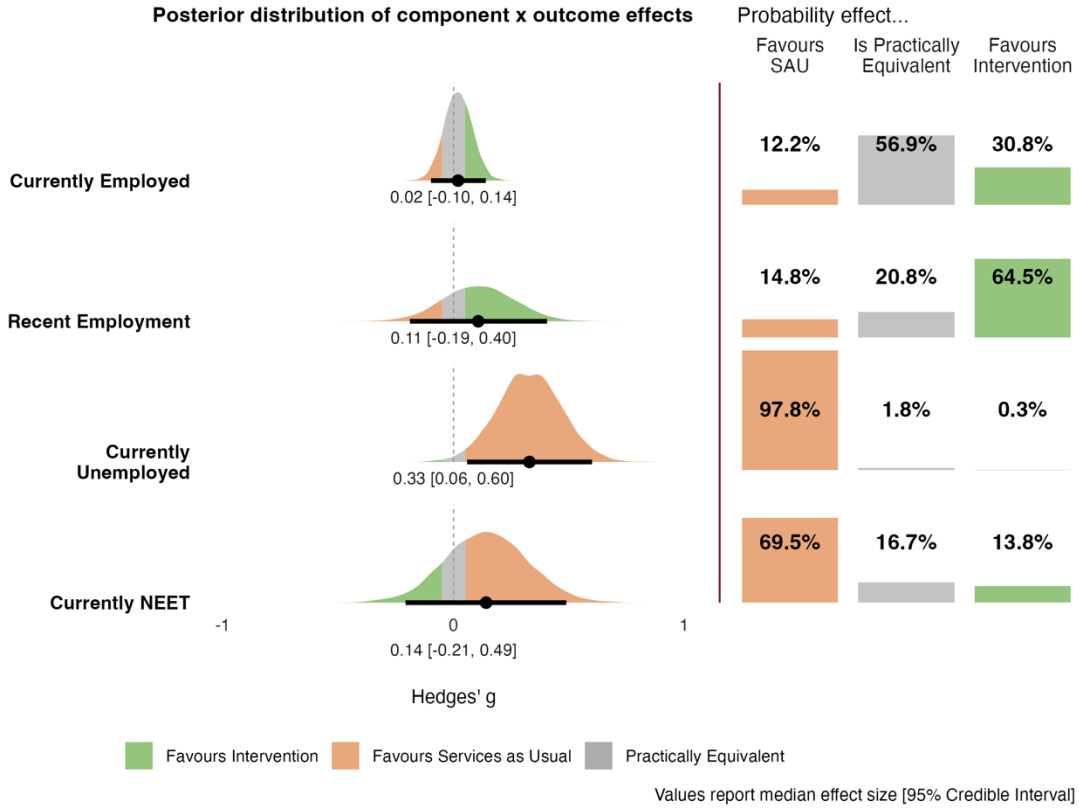


Labour Force status

The impact of Basic Skills Training on labour force outcomes is presented in Figure 10.

- Median effects vary across outcomes. Effects favour SAU for Currently Unemployed (high impact) and Currently NEET (medium impact). For Recent Employment, the median effect favours the intervention and lies in the medium-impact range. For Currently Employed, the median effect lies within the ROPE, indicating little or no effect.
- The largest probability of an effect favouring the intervention is for Recent Employment (64.5%). There is a greater than even chance (56.5%) that the effect on Currently Employed is practically equivalent. The effect on Currently Unemployment almost certainly (97.8%) favours SAU, with Currently NEET (69.5%) also favours SAU over two-thirds of the time.
- The probability of medium- or high-impact effects favouring Basic Skills Training is greatest for Recent Employment (25% medium; 27% high). At the other end of the scale, there is an 83% probability of a high-impact effect favouring SAU for Currently Unemployed.
- Overall, any positive impact of Basic Skills Training appears confined to Recent Employment; for other labour force outcomes, effects are unlikely to favour the intervention.

Figure 10 Impact of Basic Skills Training on Labour Force status

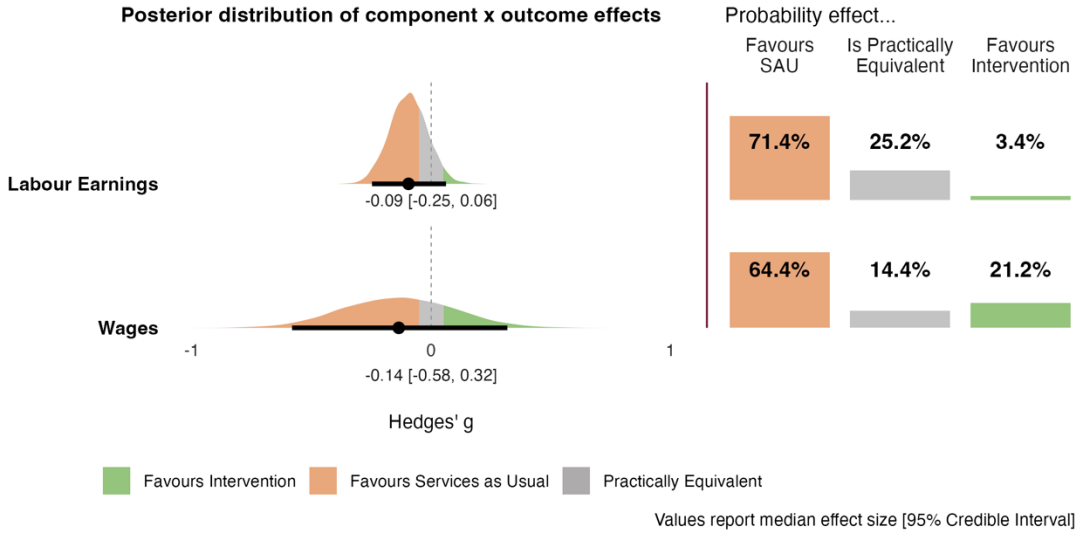


Employment compensation

The impact of Basic Skills Training on employment compensation outcomes is presented in Figure 11.

- Median effects for both outcomes favour SAU. For Labour Earnings, the median effect lies in the low-impact range while for Wages, it is medium-sized.
- The largest probability of an effect exceeding the ROPE is in a negative direction for both outcomes, favouring SAU. This probability is 71.4% for Labour Earnings and 64.4% for Wages.
- The probability of medium or high impacts favouring Basic Skills Training is very low across both outcomes (<10%).
- Overall, these results suggest that Basic Skills Training is unlikely to improve employment compensation outcomes.

Figure 11 Impact of Basic Skills Training on Employment compensation

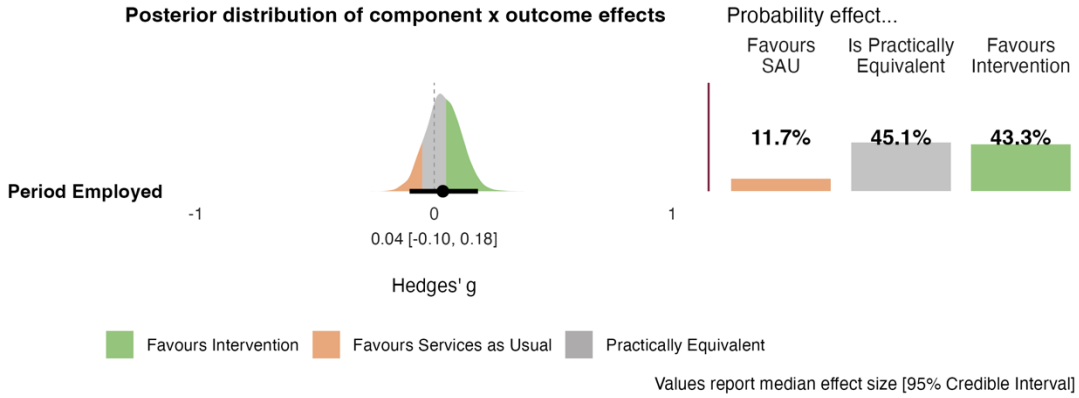


Employment duration

The impact of Basic Skills Training on employment duration outcomes is presented in Figure 12.

- The median estimate for Period Employed falls within the ROPE indicating little or no impact.
- The probability of that the impact of Basic Skills Training is practically equivalent to SAU is 45.1%.
- The probability of a medium impact is modest (19%), while a high impact is very unlikely (1%).
- Overall, Basic Skills Training may slightly increase time spent in employment, but impacts are most likely to be low in magnitude.

Figure 12 Impact of Basic Skills Training on Employment duration

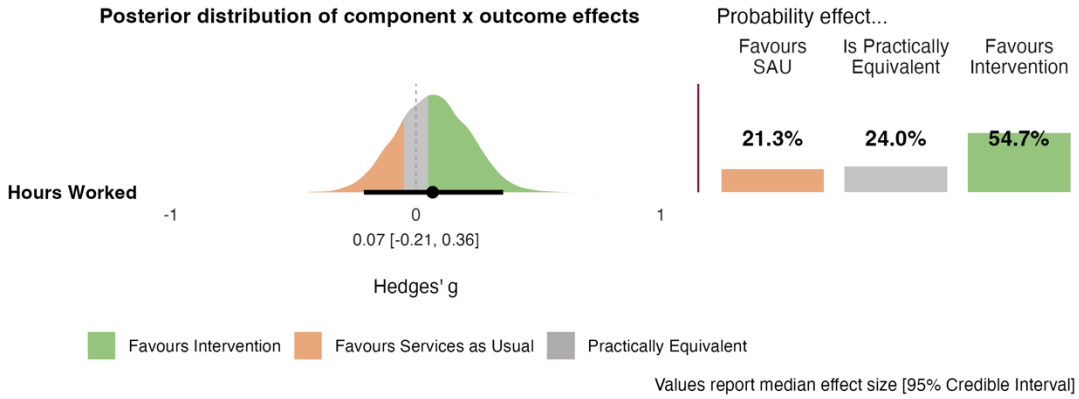


Hours worked

The impact of Basic Skills Training on *Hours Worked* is presented in Figure 13.

- The median estimate falls within the low impact range.
- The probability that it favours the intervention is 54.7%.
- There is a probability of a medium (22%) or high (19%) positive impact is about 40%.
- Overall, Basic Skills Training shows some chance of increasing hours worked.

Figure 13 Impact of Basic Skills Training on Hours worked



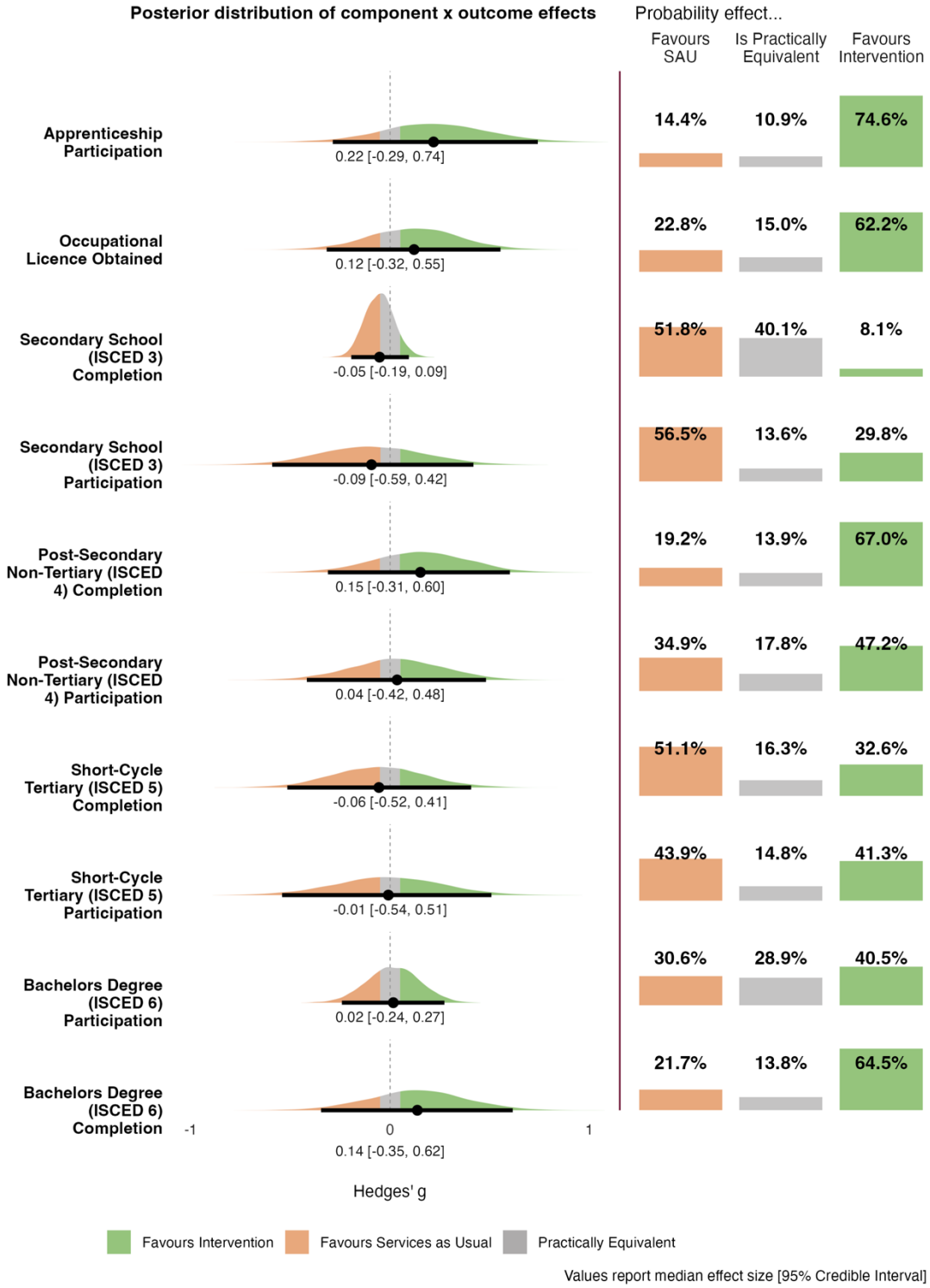
Education and Skills

The impact of Basic Skills Training on education and skills outcomes is presented in Figure 14. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls in the high impact range (*g*=0.22), with a 74.6% probability that it favours the intervention. There is a 53% probability of a high impact, making this the strongest education-related effect.
- *Occupational licence attainment* — the median estimate falls in the medium impact range (*g*=0.12), with a 62.2% probability of any positive effect. The probability of a medium or high impact is around 50% overall.
- *Secondary school completion* — the median effect is small and favours SAU (*g*=-0.05), with only a 51.8% probability of an effect favouring SAU.
- *Bachelor's degree participation* — the median estimate lies in the range of little or no effect.

Overall, while most education outcomes are likely to be low or uncertain, the results suggest Basic Skills Training may meaningfully increase apprenticeship participation and, to a lesser extent, occupational licence attainment.

Figure 14 Impact of Basic Skills Training on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect between females and males falls in the low effect range: *g*=0.08, 95% CrI [~0.00, 0.16].
- **Posterior probabilities** — there is a 97.4% chance the impact of basic skills training is higher in all-female study populations and a 2.6% chance that they are larger in all-male ones.

As mentioned in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=-0.02 95% CrI [-0.07, 0.04] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.13, 95% CrI [-0.55, 0.31].
- **Posterior probabilities** — there is a 27% chance the impact of Basic Skills Training increases with the mean study age.

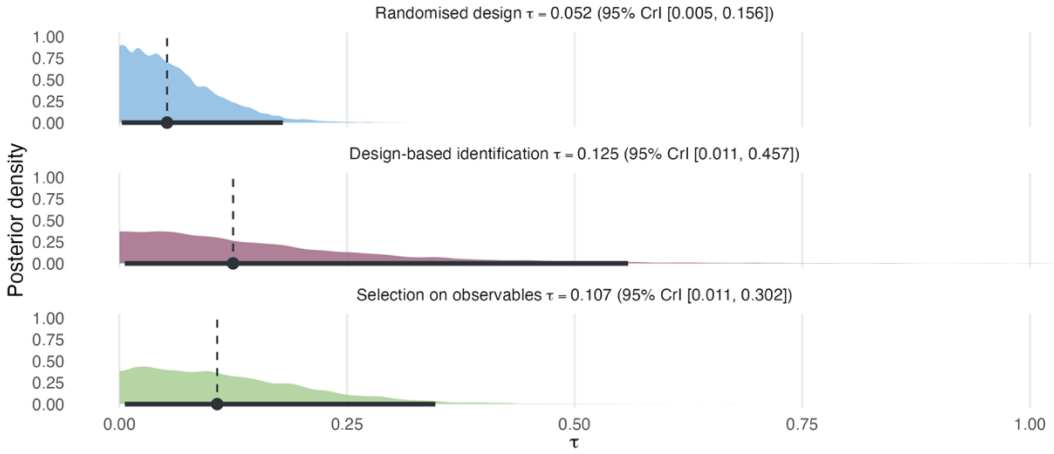
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 15 shows the component-specific heterogeneity by study design. Mirroring the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for each distribution is very close to the overall pattern, indicating no meaningful departure from the suggestion that SOO and DBI studies show greater variability.

Figure 15 Posterior distribution of between study heterogeneity (τ) by for Basic Skills Training by study design



Soft Skills Training

Key findings

- **Most results show little or no impact**. Medium- or high-impact effects are uncommon, with two exceptions: wages, which is highly likely to favour the intervention (Pr > 0 = 0.86), and be medium or large in size (81%), and apprenticeship participation, which is likely (Pr > 0.05 = 0.75) to favour the intervention and be medium or large in size (69%).
- **Positive labour-market effects are limited, but education pathways and compensation appear more promising**. As with Basic Skills Training, improvements in apprenticeship participation suggest Soft Skills Training may support longer-term labour market progression indirectly.
- **Impacts vary by population**. Effects are very likely (82%) larger in all-male study populations. There is also evidence that impacts increase as mean study age increases.
- **How to make sense of this.** Employers value soft skills and employment attributes such as the ability to work well in teams, communication skills, creativity and critical thinking. This may account for the positive wage effect observed. As with Basic Skills Training, this form of training may unlock other forms such as apprenticeship participation and attaining occupational licences that generate benefits for longer term outcomes.

Definition

Soft skills training concentrates on developing interpersonal skills. These programmes emphasise building competencies in areas such as communication, teamwork, collaboration, problem-solving, decision-making, critical thinking, and analysis.

Evidence profile

A summary of the evidence used to inform the analysis of Soft Skills Programmes is summarised in Table 23. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 23 Evidence profile for Soft Skills Training

SUMMARY	COUNT			
Number of studies	46			
Number of effect sizes	180			
Study design	RE: 32	SOO: 9	DBI: 5	
Risk of bias	Acceptable: 30		High: 16	
Study design x risk of bias	Acceptable High	RE: 25 RE: 7	SOO: 2 SOO: 7	DBI: 3 DBI: 2
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=29); Recent employment (n=12); Currently Unemployed (n=6); Currently NEET (n=1); Currently Not in the Labour Force (n=4)			
Employment Compensation	Labour Earnings (n=21); Wages (n=7)			
Employment duration	Period Employed (n=6)			
Hours Worked	Hours Worked (n=10)			
Education & Skills	Secondary School (ISCED 3) Participation (n=2); Secondary School (ISCED 3) Completion (n=24); Bachelors Degree (ISCED 6) Participation (n=2); Bachelors Degree (ISCED 6) Completion (n=24); Short-Cycle Tertiary (ISCED 5) Participation (n=5); Short-Cycle Tertiary (ISCED 5) Completion (n=4); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=3); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=4); Apprenticeship Participation (n=1); Occupational Licence Obtained (n=6)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Soft Skills Training. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 16 shows the posterior probability that the effect of Soft Skills Training on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 16 Probability of the scale of impact of Soft Skills Training



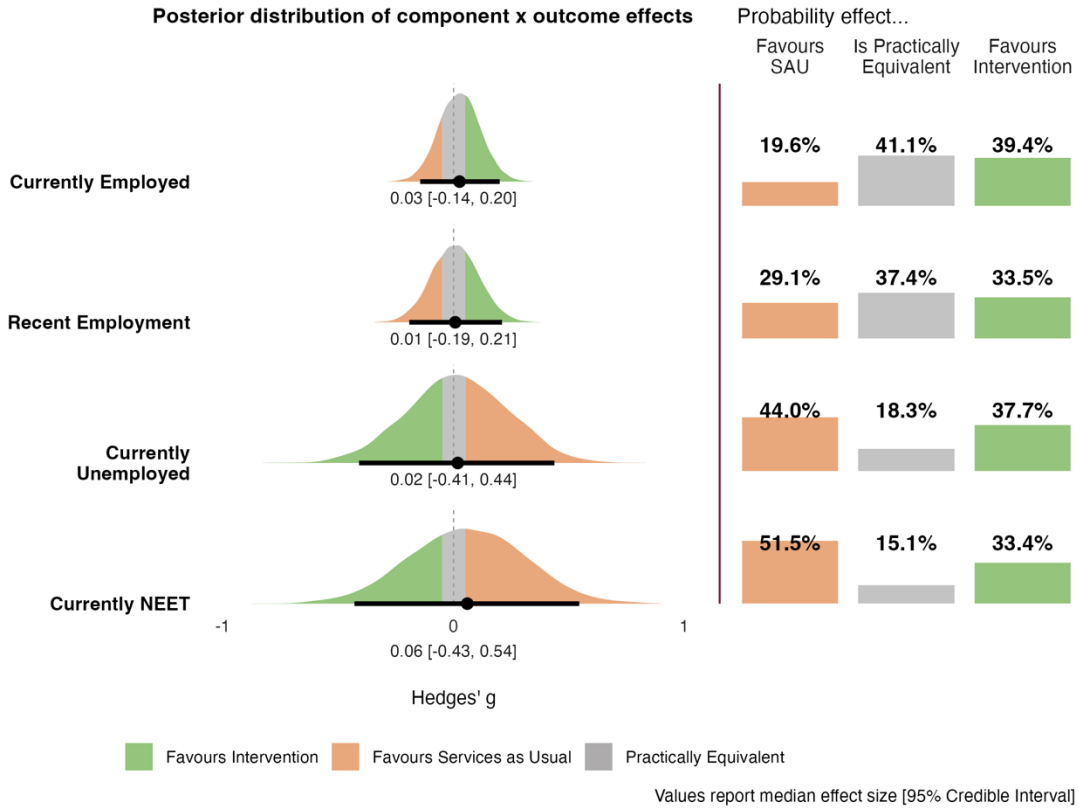
Labour Force status

The impact of Soft Skills Training on labour force outcomes is presented in Figure 17.

- Median estimates across all outcomes except Currently NEET fall within the range of little or no effect. The estimate for Currently NEET is low in magnitude and favours SAU.

- The probability that the effect favours SAU is highest for Currently NEET (51.5%) and Currently Unemployed (44%). Currently employment (41.1%) and Recent Employment (37.4%) are most likely to be practically equivalent.
- The probability of a medium or high impact is low across all outcomes.
- Overall, these findings suggest that Soft Skills Training is unlikely to have a positive impact on labour force status at 24 months.

Figure 17 Impact of Soft Skills Training on Labour Force status



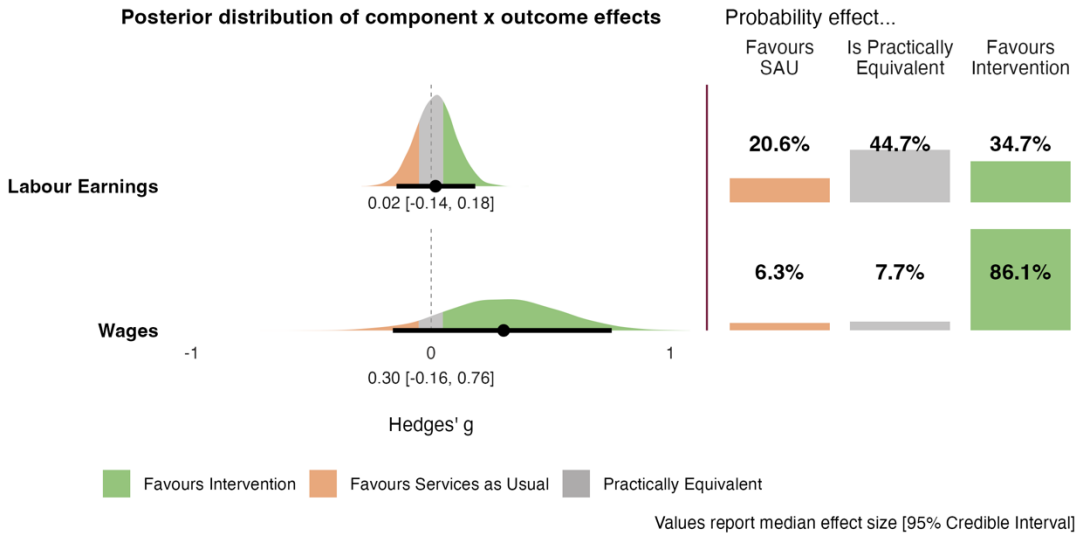
Employment compensation

The impact of Soft Skills Training on employment compensation outcomes is presented in Figure 18.

- Median estimates for labour earnings are practically equivalent, however the median for wages falls within the high impact category.
- The probability of any positive impact is very high for wages (86%) and greater than half for labour earnings (35%).

- The probability of medium or high impacts is high for wages (81%) but low for labour earnings (16%).
- Overall, these results suggest that Soft Skills Training is highly likely to have positive impact on wages.

Figure 18 Impact of Soft Skills Training on Employment compensation

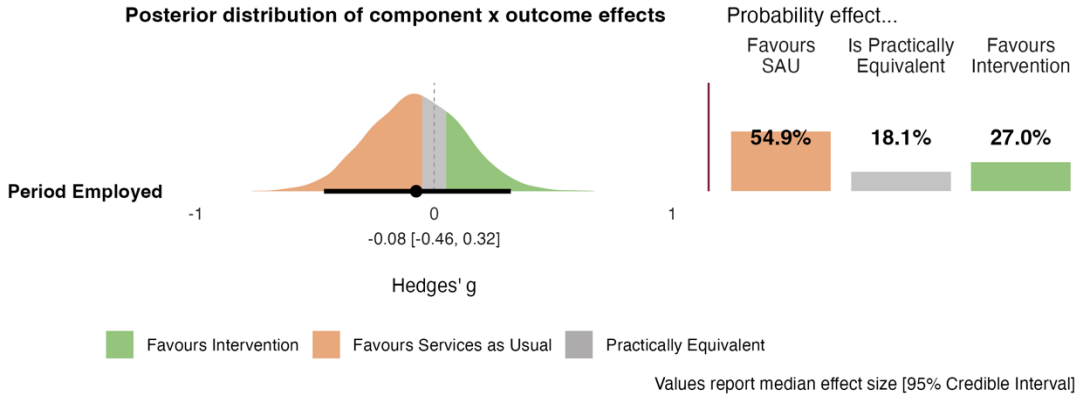


Employment duration

The impact of Soft Skills Training on employment duration outcomes is presented in Figure 19.

- The median estimate for period employed favours SAU and falls within the low impact range.
- The probability of any positive impact is 27%.
- The probability of a medium impact is modest (11%), while a high impact is very unlikely (8%).
- Overall, Soft Skills Training is unlikely to increase time spent in employment.

Figure 19 Impact of Soft Skills Training on Employment duration

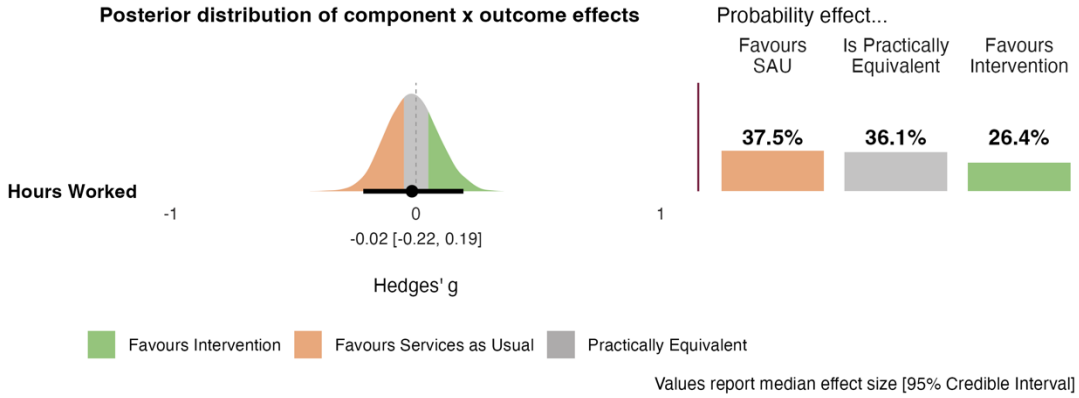


Hours worked

The impact of Soft Skills Training on hours worked is presented in Figure 20.

- The median estimate is suggests that that Soft Skills Training is practically equivalent to SAU.
- The probability of a result favouring the intervention is 26.4%.
- The probability of a medium (11%) or high (2%) impact is low (13%).
- Overall, Soft Skills Training is unlikely to increase hours worked.

Figure 20 Impact of Soft Skills Training on Hours worked



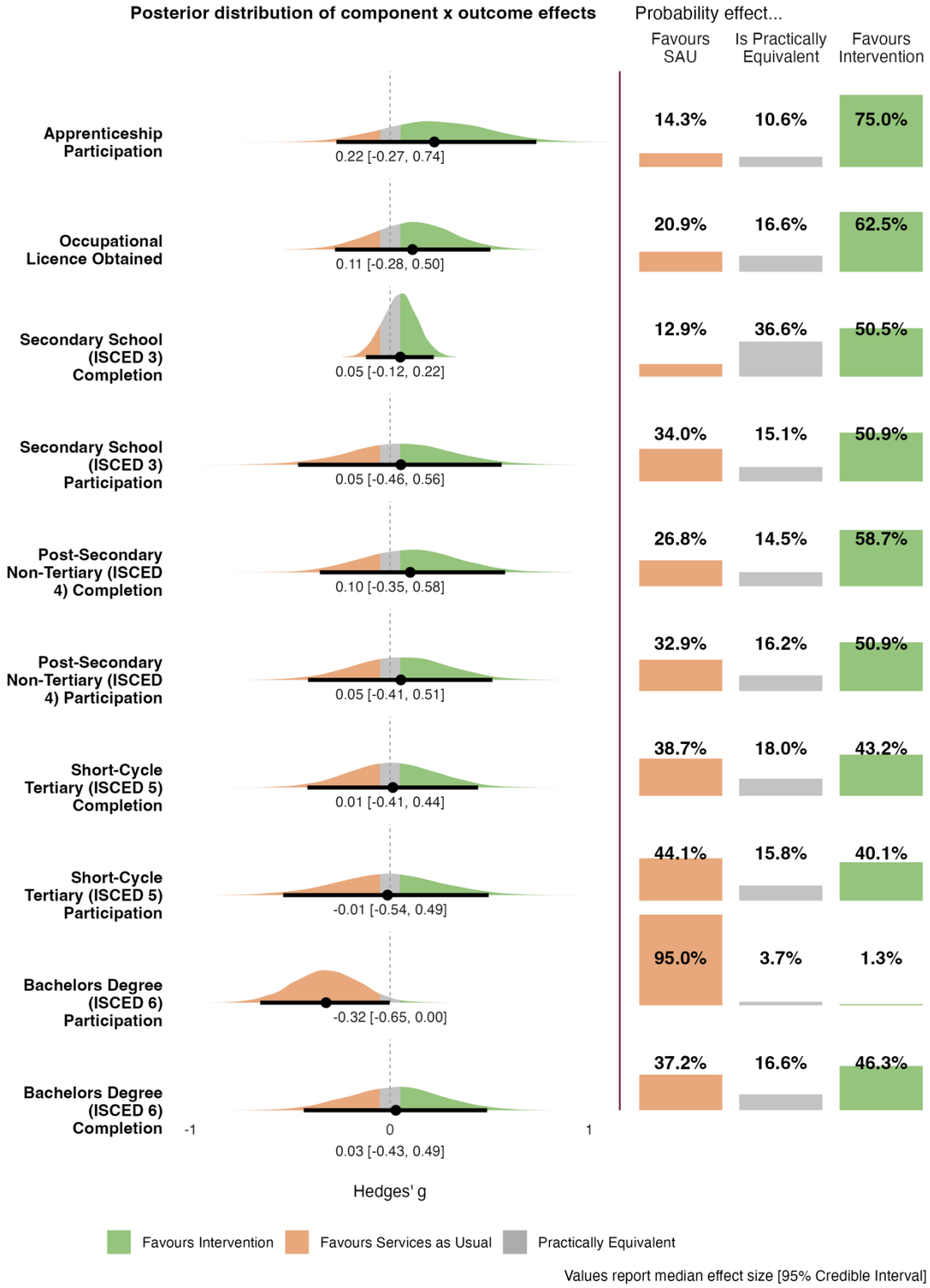
Education and Skills

The impact of Soft Skills Training on education and skills outcomes is presented in Figure 21. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls in the high impact range (g=0.22), with an 75% probability of any positive effect. There is a 54% probability of a high impact, making this the strongest education-related effect.
- *Occupational licence attainment* — the median estimate falls in the medium-sized impact range (g=0.11), with a 63% probability of any positive effect. The probability of a medium or high impact is around 50% overall.
- *Secondary school completion* — the median effect is low (g=0.05), however there is a 51% probability of a positive impact.
- *Bachelor's Degree Participation* — the median estimate is high (g=-0.32) and favours SAU.

Overall, while most education outcomes are likely to be low or uncertain, the results suggest Soft Skills Training may meaningfully increase apprenticeship participation, occupational licence attainment and to a lesser extent, secondary school completion.

Figure 21 Impact of Soft Skills Training on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of soft skills training between females and males falls within the no or low effect range: *g*=-0.04, 95% CrI [-0.13, 0.05].
- **Posterior probabilities** — there is an 18.4% chance the impact of soft skills training is higher in all-female study populations and an 81.6% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=0.03, 95% CrI [-0.03, 0.09] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.26, 95% CrI [-0.24, 0.74].

- **Posterior probabilities** — there is an 84.7% chance the impact of Soft Skills Training increases with the mean study age.

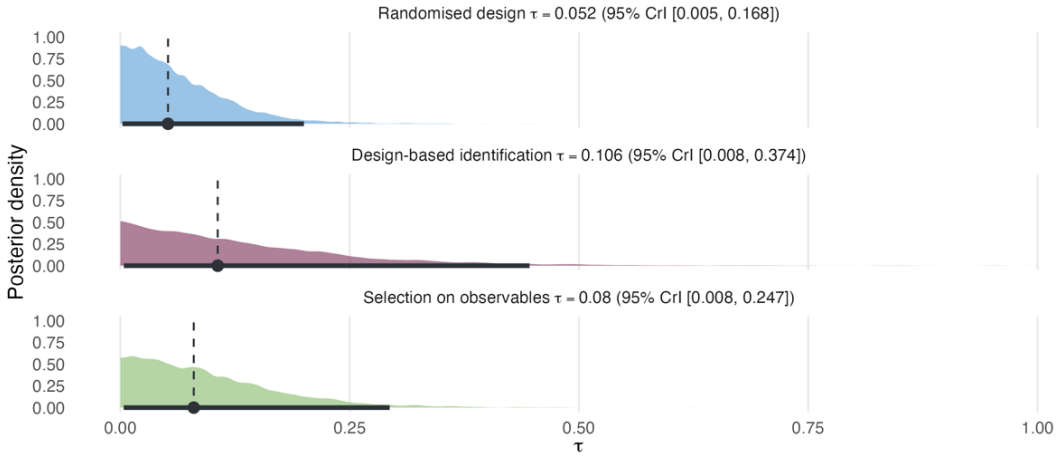
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 22 shows the component-specific heterogeneity by study design. Mirroring the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for each distribution is slightly higher the overall results, however there is no meaningful change from the conclusion that SOO and DBI studies show greater variability.

Figure 22 Posterior distribution of between study heterogeneity (τ) by for Soft Skills Training by study design



Behavioural Skills Training

Key findings

- **Behaviour Skills Training shows consistently large and beneficial effects on education outcomes.** Median effects are high for apprenticeship participation (Pr > 0.05 = 0.74; Pr > 0.2 = 0.53), secondary school completion (Pr > 0.05 ~ 1; Pr > 0.2 = 0.8), and bachelor's degree participation (Pr > 0.2 = 0.90), indicating a high likelihood that impacts favour the intervention and are large in magnitude.
- **Positive impacts on Wages and Hours Worked**. There is a high (72%) probability of a positive impact on Hours Worked, and a reasonable chance (60%) that that impact is medium or high in size. Similarly, there is a decent (68%) probability of a positive impact on Wages, and a greater than even chance (58%) that that impact is medium or large in magnitude.
- **Impacts vary by population**. Effects are very likely (98%) to be larger in all-male study populations. There is also evidence that impacts increase as mean study age increases.
- **How to make sense of this.** This intervention may have enabled young people to better thrive in the discipline-context of educational institutions. Achieving improved qualification levels from education participation delivers better long-term economic and social outcomes for individuals. Employers look for people who understand the behaviours required by the workplace. Improved behavioural skills in the workplace may increase employer trust and confidence which may lead to increased working hours and improved wages. Impacts on secondary school completion are also worth understanding further, potentially impacted by study populations included.

Definition

Behavioural skills training focuses on instilling positive work habits, attitudes, and behaviours that are crucial for success in the workforce. These programmes cover aspects such as punctuality, appropriate language, dress and communication, professionalism, and adherence to workplace norms and expectations.

Evidence profile

A summary of the evidence used to inform the analysis of Behavioural Skills Programmes is summarised in Table 24. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 24 Evidence profile for Behavioural Skills Training

SUMMARY	COUNT			
Number of studies	49			
Number of effect sizes	189			
Study design	RE: 35	SOO: 9	DBI: 5	
Risk of bias	Acceptable: 35		High: 14	
Study design x risk of bias	Acceptable High	RE: 30 RE: 5	SOO: 2 SOO: 7	DBI: 3 DBI: 2
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=30); Recent Employment (n=11); Currently Unemployed (n=6); Currently NEET (n=1); Currently Not in the Labour Force (n=4)			
Employment Compensation	Labour Earnings (n=21); Wages (n=8)			
Employment duration	Period Employed (n=7)			
Hours Worked	Hours Worked (n=9)			
Education & Skills	Secondary School (ISCED 3) Participation (n=3); Secondary School (ISCED 3) Completion (n=25); Bachelors Degree (ISCED 6) Participation (n=13); Bachelors Degree (ISCED 6) Completion (n=8); Short-Cycle Tertiary (ISCED 5) Participation (n=4); Short-Cycle Tertiary (ISCED 5) Completion (n=6); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=4); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=4); Apprenticeship Participation (n=1); Occupational Licence Obtained (n=7)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Behavioural Skills Training. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

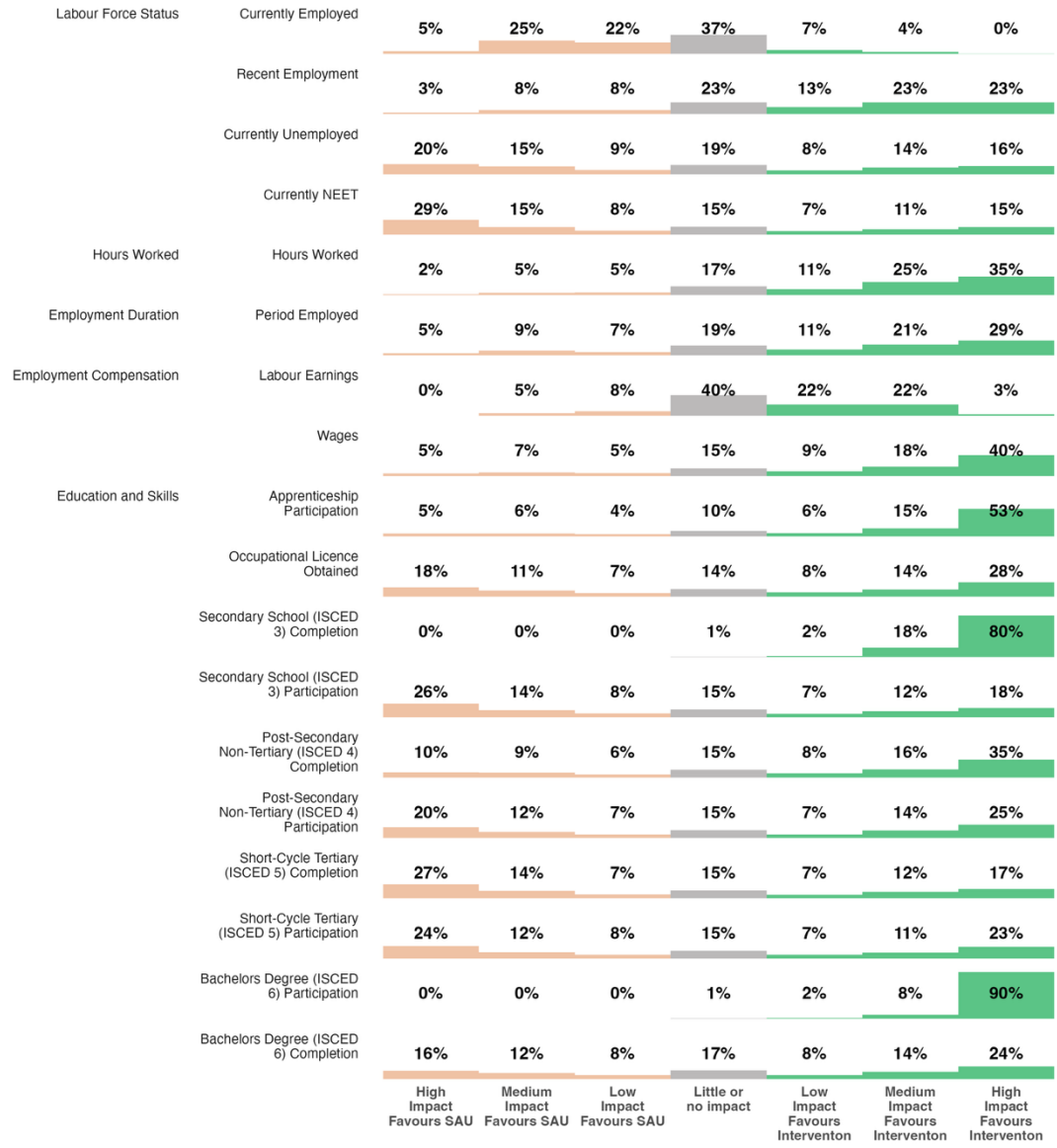
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 23 shows the posterior probability that the effect of Behavioural Skills Training on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 23 Probability of the scale of impact of Behavioural Skills Training



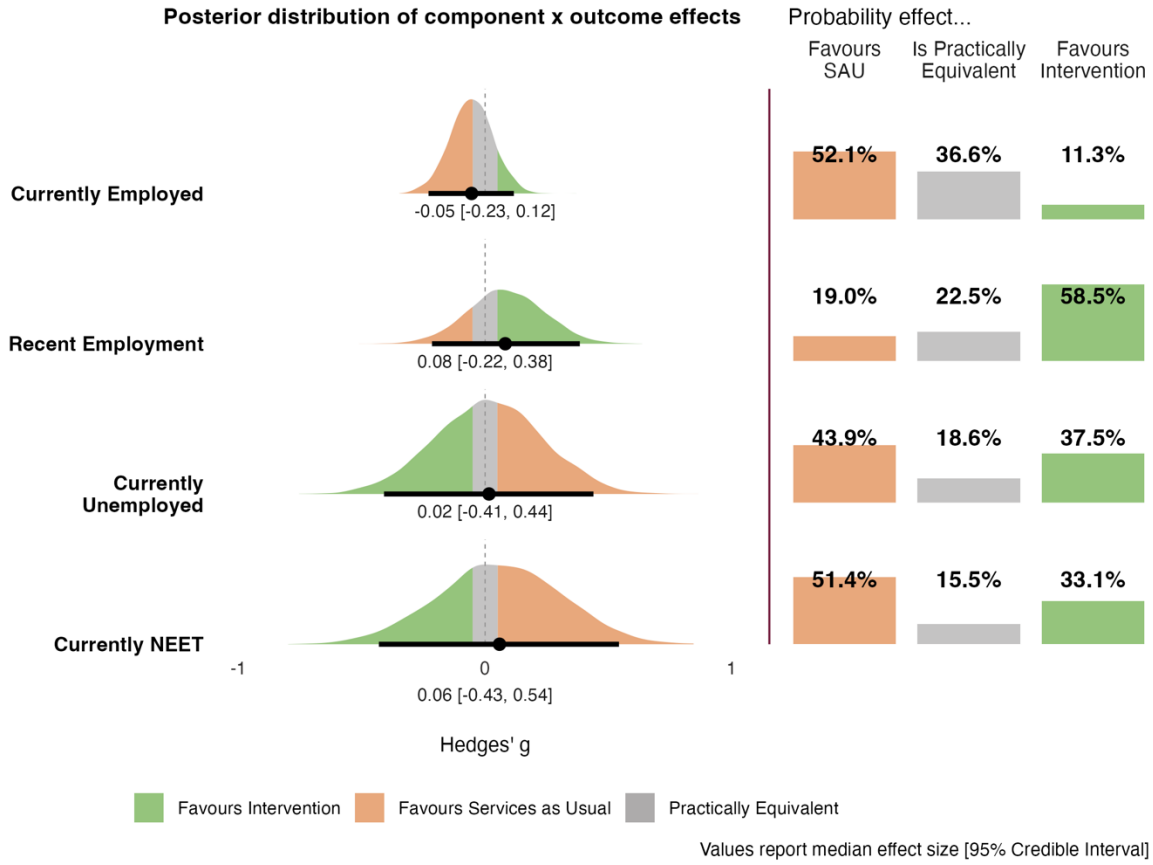
Labour Force status

The impact of Behavioural Skills Training on labour force outcomes is presented in Figure 24.

- Median estimates across all four outcomes fall within the low or little or no impact range. Results for Currently Employed and Currently NEET both favour SAU with a low impact magnitude.

- The highest probability for three outcomes favours SAU: Currently Employed (52%), Currently NEET (51.4%) and Currently Unemployed (44%). The only outcome with a modal result favours the intervention is Recent Employment (59%).
- The probability of a medium or high impact favour the intervention is low. There is a reasonable chance of a high or medium impact favouring SAU for Currently NEET (44%) and Currently Unemployed (35%).
- Overall, these findings suggest that Behavioural Skills Training may have a positive impact on Recent Employment, though across outcomes impacts are most likely to fall within the low range, with medium or high impacts unlikely.

Figure 24 Impact of Behavioural Skills Training on Labour Force status

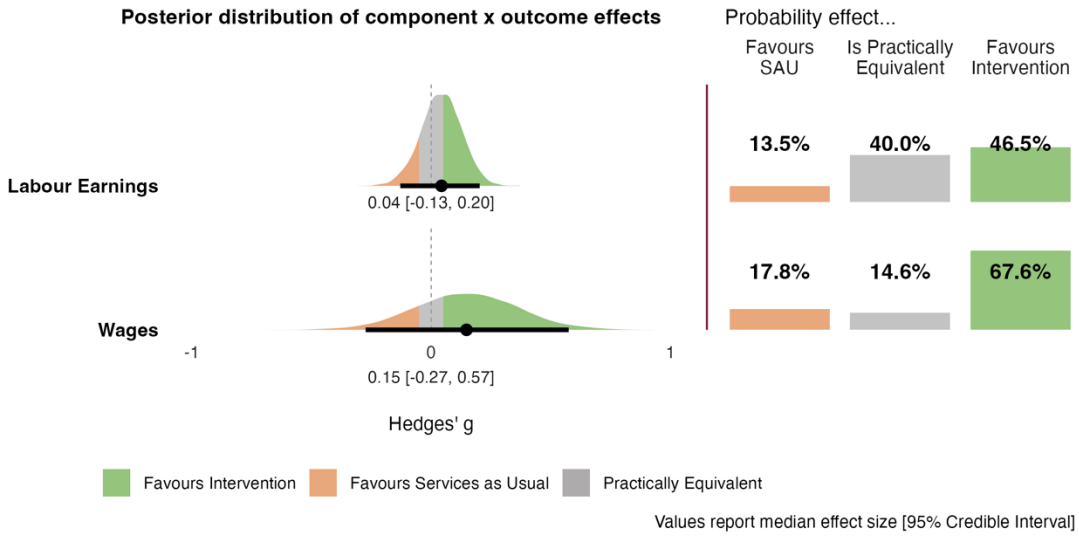


Employment compensation

The impact of Behavioural Skills Training on employment compensation outcomes is presented in Figure 25.

- Median estimates for Labour Earnings fall within the little or no impact range, but the median impact for Wages is medium-sized.
- The probability of any positive impact is greater than two in three for Wages (68%) and almost half (47%) for Labour Earnings.
- The probability of medium or high impacts is low for Labour Earnings (25%) but greater than half for Wages (58%).
- Overall, these results suggest that Behavioural Skills Training can improve employment compensation.

Figure 25 Impact of Behavioural Skills Training on Employment compensation



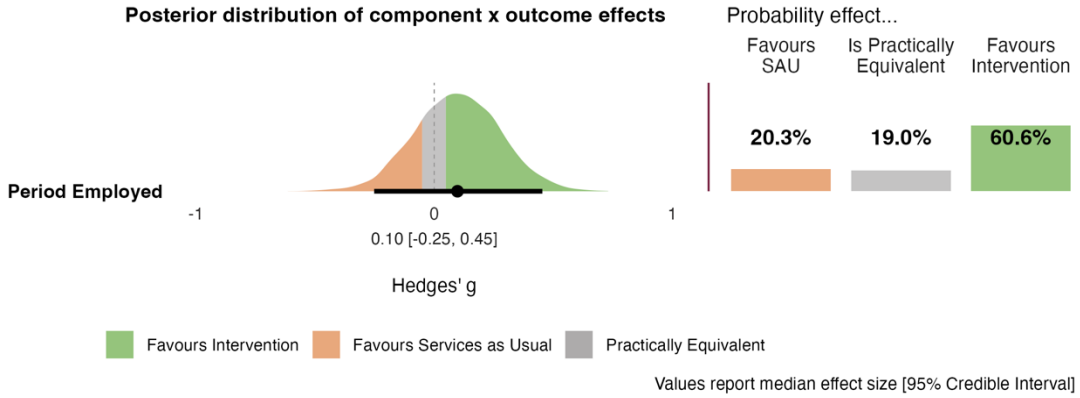
Employment duration

The impact of Behavioural Skills Training on employment duration outcomes is presented in Figure 26.

- The median estimate for Period Employed falls just on the threshold of medium-sized impact.
- The probability of any positive impact is 61%.

- The probability of a medium (21%) or high (29%) impact is exactly even (50%).
- Overall, Behavioural Skills Training can increase time spent in employment.

Figure 26 Impact of Behavioural Skills Training on Employment duration

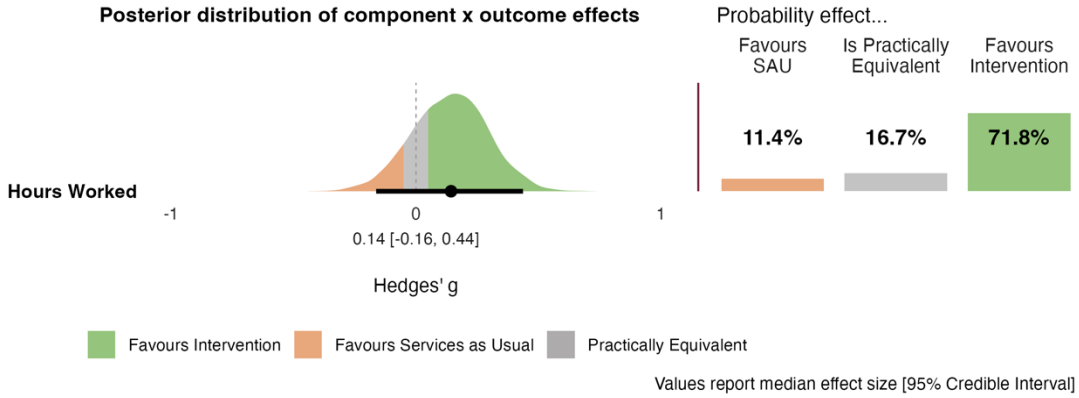


Hours worked

The impact of Behavioural Skills Training on hours worked is presented in Figure 27.

- The median estimate for Hours Worked falls within the medium impact range.
- The probability of any positive impact is 72%.
- The probability of a medium (25%) or high (35%) impact is around 60%.
- Overall, Behavioural Skills Training shows a good chance of increasing hours worked.

Figure 27 Impact of Behavioural Skills Training on Hours worked



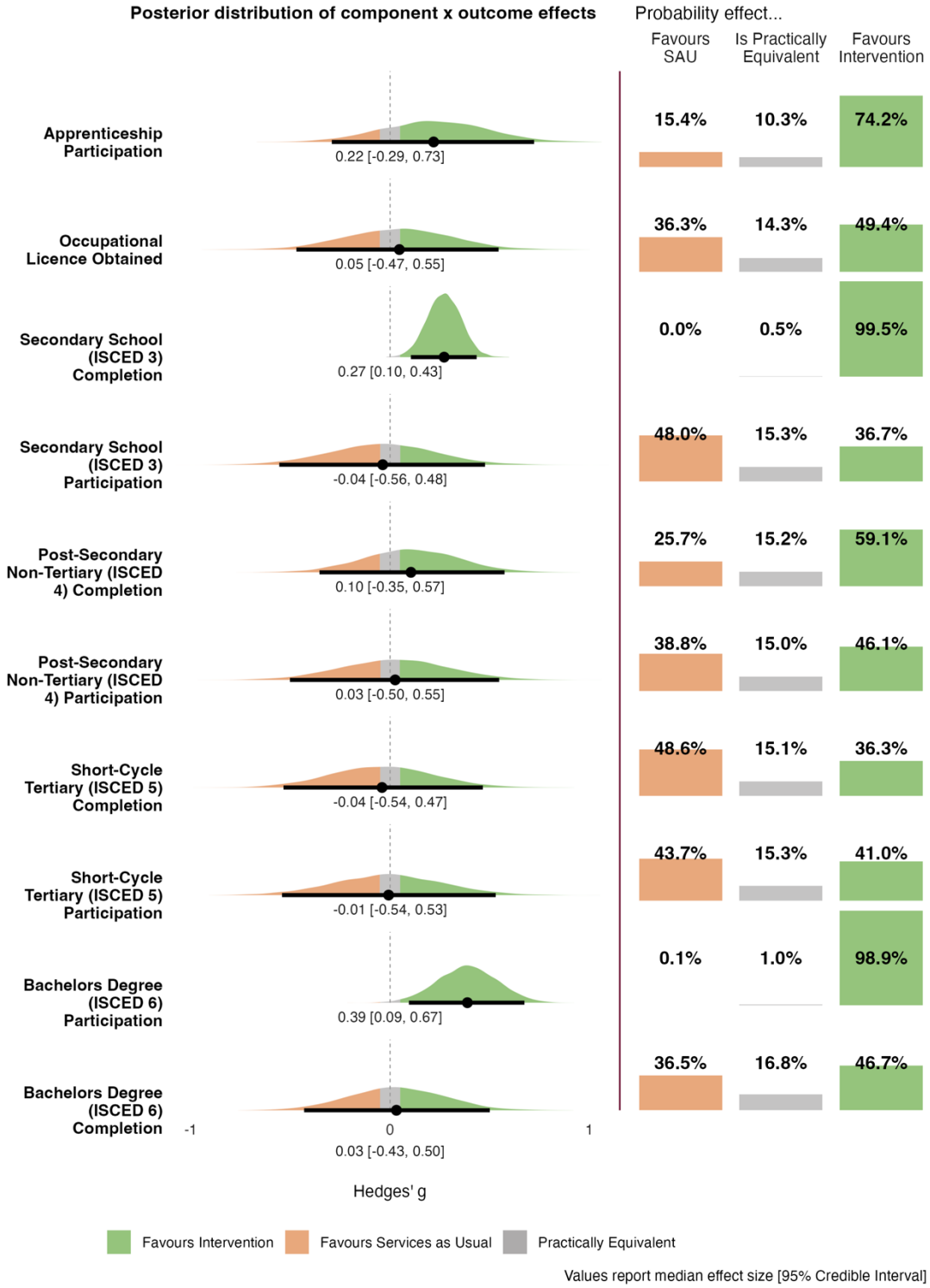
Education and Skills

The impact of Behavioural Skills Training on education and skills outcomes is presented in Figure 28. Because there is a wide range of outcomes, we focus here on three that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls in the high impact range (g=0.22), with an 74% probability of any positive effect. There is a 53% probability of a high impact.
- *Occupational Licence Obtained* — the median estimate falls in the low impact range (g=0.05). The roughly a one-in-two chance (Pr > 0.05 = 0.49) that the impact favours the intervention.
- *Secondary school completion* — the median effect is high (g=0.27), with almost a 100% probability of any positive effect. There is a high probability (80%) of a high impact.
- *Bachelor's degree participation* — the median effect is high (g=0.39) with a very high probability (90%) of a high impact.

Overall, Behavioural Skills Training is very highly likely to have a substantial positive impact on secondary school completion and participation in a bachelor'sbachelor's degree.

Figure 28 Impact of Behavioural Skills Training on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of behavioural skills training between females and males falls in the low effect range: *g*=-0.09, 95% CrI [-0.17, -0.01].
- **Posterior probabilities** — there is 1.8% chance the impact of behavioural skills training is higher in all-female study populations and a 98.2% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=-0.01, 95% CrI [-0.07, 0.05] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.08, 95% CrI [-0.59, 0.42].

- **Posterior probabilities** — there is a 37% chance the impact of Behavioural Skills Training increases with the mean study age.

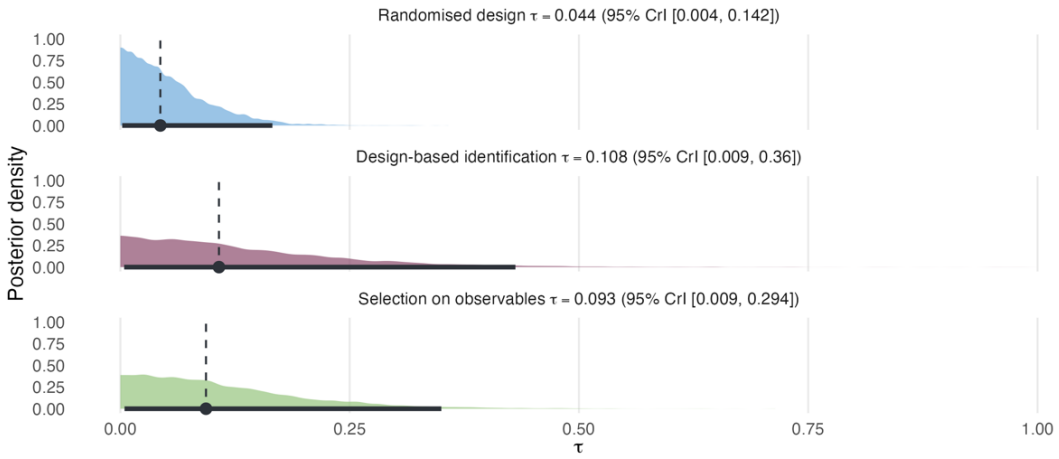
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 29 shows the component-specific heterogeneity by study design. Mirroring the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for each distribution is slightly smaller the overall results, however there is no meaningful change from the conclusion that SOO and DBI studies show greater variability.

Figure 29 Posterior distribution of between study heterogeneity (τ) by for Behavioural Skills Training by study design



Job Specific Technical Skills (Off-the-Job Training)

Key findings

- **Job Specific Technical Skills (Off-the-Job Training) has a positive impact on education and skills outcomes.** Median effects are high for Occupational Licence Obtainment (Pr > 0.05 = 0.75; Pr > 0.2 = 0.53), and medium for Secondary School Completion (Pr > 0.05 = 0.94; Pr > 0.1 = 0.78), and Bachelor's degree Completion (Pr > 0.05 = 0.70; Pr > 0.1 = 0.6), indicating a high likelihood that impacts favour the intervention and are at least medium in magnitude.
- **Positive impacts on Wages**. There is a high (78%) probability of a positive impact on Wages, but the impact is most likely to be low or medium in magnitude.
- **Impacts vary by population**. Effects are very likely (98%) to be larger in all-male study populations, however the difference is low in magnitude. Effects are also likely to increase as mean study age increases with a medium sized magnitude difference between a mean study age of 24 vs. 16.
- **How to make sense of this.** This component explores off-the-job training in isolation rather than as part of a package involving work or work experience or on-the-job learning (such as an apprenticeship). While it is intuitive that there is an effect on occupational licence attainment, it is less clear why effects on secondary school completion and bachelor's degree participation emerge. This merits further exploration. Obtaining an occupational licence is anticipated to create longer term labour market effect and in general, attainment of higher levels of education also supports better long-term labour market and social outcomes.

Definition

Job-specific technical/vocational skills training, delivered in an off-job setting, focuses on equipping participants with specialised knowledge and competencies required for specific occupations or industries. These programmes adopt a "train first, then place" approach, where individuals receive intensive, often full-time, training in a classroom or educational setting before transitioning into employment.

Evidence profile

A summary of the evidence used to inform the analysis of Job Specific Technical Skills (Off-the-Job Training) is summarised in Table 25. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 25 Evidence profile for Job Specific Technical Skills (Off-the-Job Training)

SUMMARY	COUNT			
Number of studies	41			
Number of effect sizes	106			
Study design	RE: 15	SOO: 21	DBI: 5	
Risk of bias	Acceptable: 25		High: 16	
Study design x risk of bias	Acceptable High	RE: 12 RE: 3	SOO: 10 SOO: 11	DBI: 3 DBI: 2
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=28); Recent Employment (n=7); Currently Unemployed (n=2); Currently NEET (n=1); Currently Not in the Labour Force (n=1)			
Employment Compensation	Labour Earnings (n=12); Wages (n=3)			
Employment duration	Period Employed (n=3)			
Hours Worked	Hours Worked (n=4)			
Education & Skills	Secondary School (ISCED 3) Participation (n=1); Secondary School (ISCED 3) Completion (n=11); Bachelors Degree (ISCED 6) Participation (n=7); Bachelors Degree (ISCED 6) Completion (n=4); Short-Cycle Tertiary (ISCED 5) Participation (n=2); Short-Cycle Tertiary (ISCED 5) Completion (n=3); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=5); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=1); Occupational Licence Obtained (n=2)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Job Specific Technical Skills (Off-the-Job Training). For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 30 shows the posterior probability that the effect of Job Specific Technical Skills (Off-the-Job Training) on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 30 Probability of the scale of impact of Job Specific Technical Skills (Off-the-Job Training)

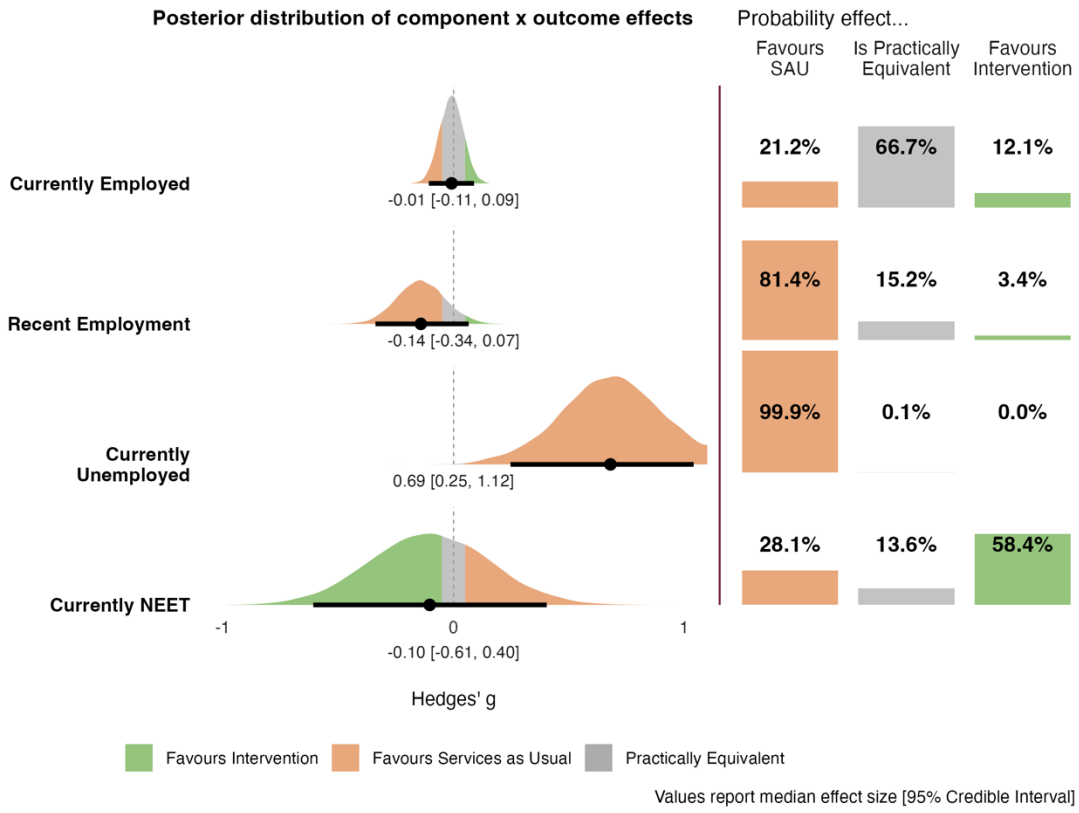


Labour Force status

The impact of Job Specific Technical Skills (Off-the-Job Training) on labour force outcomes is presented in Figure 31.

- There is a high impact on Current Unemployment, favouring SAU.
- There is a medium-sized impact on Currently NEET, favouring the intervention. The probability it favours the intervention is 58%, and there is a 51% chance that the impact is either high (36%) or medium (15%).
- There is likely (67%) little or no impact on Currently Employed, any positive impact is almost certain to be low.
- Overall, these findings suggest that Job Specific Technical Skills (Off-the-Job Training) has a complex impact on labour force status. Impacts favouring SAU on current unemployment are very high, while also reducing current NEET status, suggesting that this component may lead to displacement from the labour force into education or training and delays to entering employment. This finding chimes with long-standing evidence on the limited impact and high cost off-the-job training programmes in ALMP and recommendations that use of this measure be small in scale and closely targeted to the needs of local employers and job seekers (Meager, 2009; Kluve *et al.*, 2017; Card, Kluve and Weber, 2018; Ghisletta, Kemper and Stöterau, 2022).

Figure 31 Impact of Job Specific Technical Skills (Off-the-Job Training) on Labour Force status

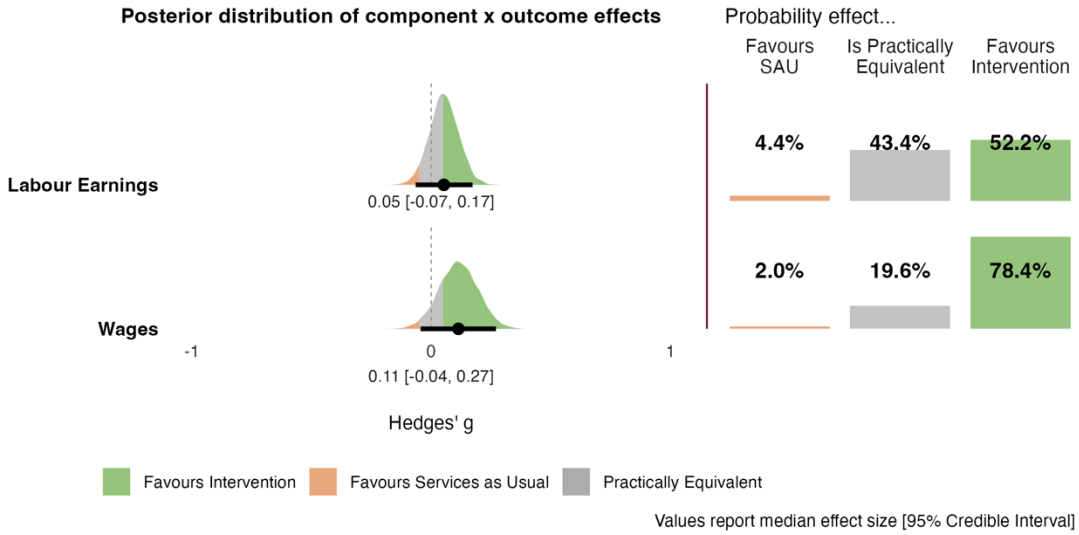


Employment compensation

The impact of Job Specific Technical Skills (Off-the-Job Training) on employment compensation outcomes is presented in Figure 32.

- Median estimates for both labour earnings and wages fall within the low and medium impact range.
- The probability of a positive impact for Labour Earnings (Pr > 0.05 = 52) and Wages (Pr> 0.05 = 0.78) is both high.
- The probability of a medium or high impact is relatively low for Labour Earnings (Pr > 0.01 = 22), but for Wages is greater than half (Pr > 0.1 = 0.56).
- Overall, these results suggest little evidence that Job Specific Technical Skills (Off-the-Job Training) has is likely to have small or medium sized impact on employment compensation.

Figure 32 Impact of Job Specific Technical Skills (Off-Job Training) on Employment compensation

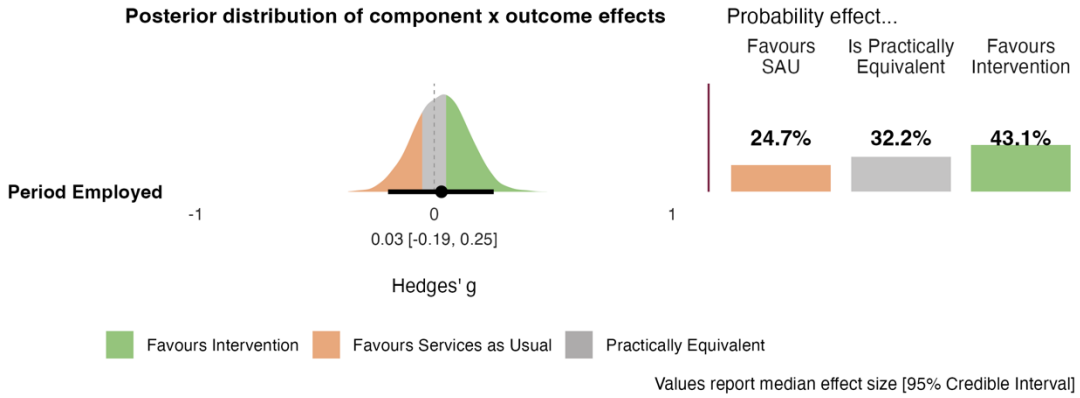


Employment duration

The impact of Job Specific Technical Skills (Off-the-Job Training) on employment duration outcomes is presented in Figure 33.

- The median estimate for Period Employed falls within the little or no impact range.
- The probability the impact favours the intervention is 43%.
- The probability of a medium impact is modest (20%), while a high impact is very unlikely (7%).
- Overall, Job Specific Technical Skills (Off-the-Job Training) may slightly increase time spent in employment, but any positive impacts are most likely to be low in magnitude.

Figure 33 Impact of Job Specific Technical Skills (Off-the-Job Training) on Employment duration

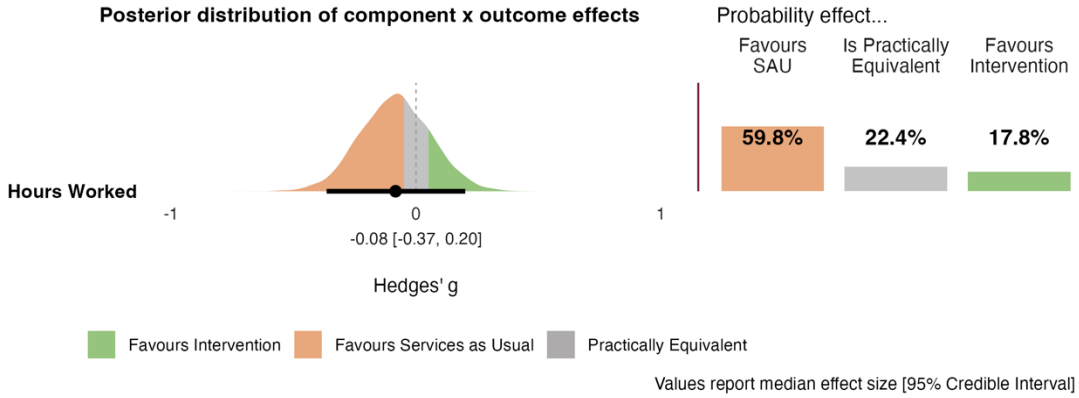


Hours worked

The impact of Job Specific Technical Skills (Off-the-Job Training) on Hours Worked is presented in Figure 34.

- The median estimate for Hours Worked falls within the low impact range and favours SAU.
- The probability that the result favours SAU is more than half (Pr < 0.05 = 0.60).
- Overall, Job Specific Technical Skills (Off-the-Job Training) has a low probability of increasing hours worked.

Figure 34 Impact of Job Specific Technical Skills (Off-Job Training) on Hours worked



Education and Skills

The impact of Job Specific Technical Skills (Off-the-Job Training) on education and skills outcomes is presented in Figure 35. Because there is a wide range of outcomes, we focus here on three that are most salient for policymakers:

- *Occupational licence attainment* — the median estimate falls in the high impact range (g=0.22), with an three-in-four chance of any positive effect (Pr > 0.05 = 0.75), and a more than even chance (Pr > 0.25 = 0.53) of a high impact.
- *Secondary school completion* — the median effect falls within the medium impact range (*g*=0.15), with a very high chance of a outcome favouring the intervention (Pr > 0.05 = 0.94), and a high chance (Pr > 0.10 = 0.78) of a medium (57%) or high (21%) effect.
- *Bachelor's degree participation* — the median estimate falls in the low impact range (*g*=0.06). The probability of a positive impact favouring the intervention is high (70%); however it is more likely to be low (29%) in magnitude than medium (26%) or high (2%).

Overall, while most education outcomes are likely to be low or uncertain, the results suggest Job Specific Technical Skills (Off-the-Job Training) may meaningfully increase secondary school completion and, to a lesser but still high extent, occupational licence attainment and bachelor's degree participation.

Figure 35 Impact of Job Specific Technical Skills (Off-the-Job Training) on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of Job Specific Technical Skills (Off-the-Job Training) between females and males falls in the low effect range: *g*=-0.07, 95% CrI [-0.13, -0.01].

- **Posterior probabilities** — there is a 1.7% chance the impact of Job Specific Technical Skills (Off-the-Job Training) is higher in all-female study populations and a 98.3% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=0.02, 95% CrI [-0.01, 0.05] per year.

- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.16, 95% CrI [-0.08, 0.43].

- **Posterior probabilities** — there is a 91% chance the impact of Job Specific Technical Skills (Off-the-Job Training) increases with the mean study age.

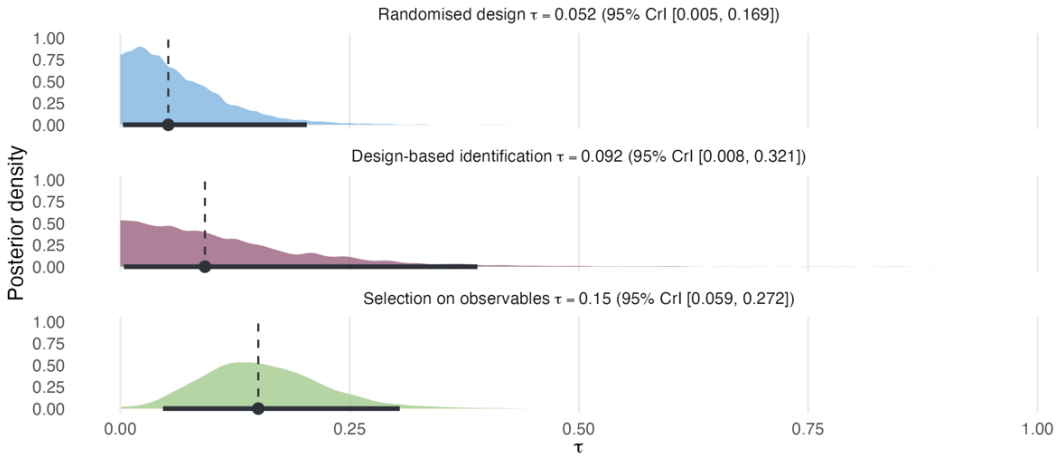
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 36 shows the component-specific heterogeneity by study design. Mirroring the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for RE's and DBI's is slightly lower the overall results. However, the median and spread of the SOO is much higher. This suggests that there is some study design dependent variability for this component, with SOO studies showing greater between-study variability.

Figure 36 Posterior distribution of between study heterogeneity (τ) by for Job Specific Technical Skills (Off-the-Job Training) by study design





Self-employment support

Meta-analysis results

Self-Employment Support

Key findings

- **Self-employment support is underexplored in high income countries.** Only five studies include self-employment support components, resulting in low certainty and requiring cautious interpretation.
- **Effects are strongly concentrated on self-employment outcomes.** For both Current Self-Employment and Current Unemployment, median effects favour the intervention and are large in magnitude, with a probability of exceeding the low-impact threshold and the high-impact threshold equal to one ($Pr > 0.05 = 1$; $Pr > 0.2 = 1$). Effects on other outcomes predominantly favour SAU, consistent with the specific aims of this intervention component.
- **Impacts vary by population characteristics**. There is a 61% probability that effects are larger in all-male study populations, though differences are small in magnitude. There is stronger evidence that impacts increase with mean study age (Pr = 75%), with a high-magnitude contrast between studies with mean ages of 24 versus 16.
- **How to make sense of this.** The limited evidence suggests that self-employment support is effective at increasing self-employment among participants but does not translate into broader gains in other employment or education and skills outcomes. Broader research into self-employment indicates that while it is motivating for some and can deliver the flexibility that some need to be able to work, it often leads to young people earning less and working longer hours compared to those in employment. The findings from this analysis point to the importance of careful targeting of self-employment support and highlight the need for both further impact evaluations and research to identify which young people may benefit most, and into the nature and quality of their self-employed roles.

Definition

Self-employment support aims to provide advisory services and facilitate access to support, finance and markets for the development or growth of youth-owned businesses or self-employment ventures. These interventions include a range of services such as business advisory and mentoring support, business skills training, access to markets and value chains, direct credit or facilitated access to credit, monetary or in-kind grants for start-up or growth, and micro-franchising initiatives or mechanisms. Self-employment

support can focus on entrepreneurship and business innovation or the skills and capabilities to offer craft and service skills through self-employment.

Evidence profile

A summary of the evidence used to inform the analysis of Self-Employment Support is summarised in

Table 26. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 26 Evidence profile for Self-Employment Support

SUMMARY	COUNT			
Number of studies	5			
Number of effect sizes	17			
Study design	RE: 1	SOO: 4	DBI: 0	
Risk of bias	Acceptable: 1		High: 4	
Study design x risk of bias	Acceptable High	RE: 0 RE: 1	SOO: 1 SOO: 3	DBI: 0 DBI: 0
Studies reporting each outcome:				
Labour Force Status	Currently Self-Employed (n=1); Currently Employed (n=4); Recent Employment (n=1); Currently Unemployed (n=3); Currently Not in the Labour Force (n=3), Employed since baseline (n=2)			
Employment duration	Period Employed (n=2)			
Education & Skills	Secondary School (ISCED 3) Completion (n=1)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Self-Employment Support. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate

mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

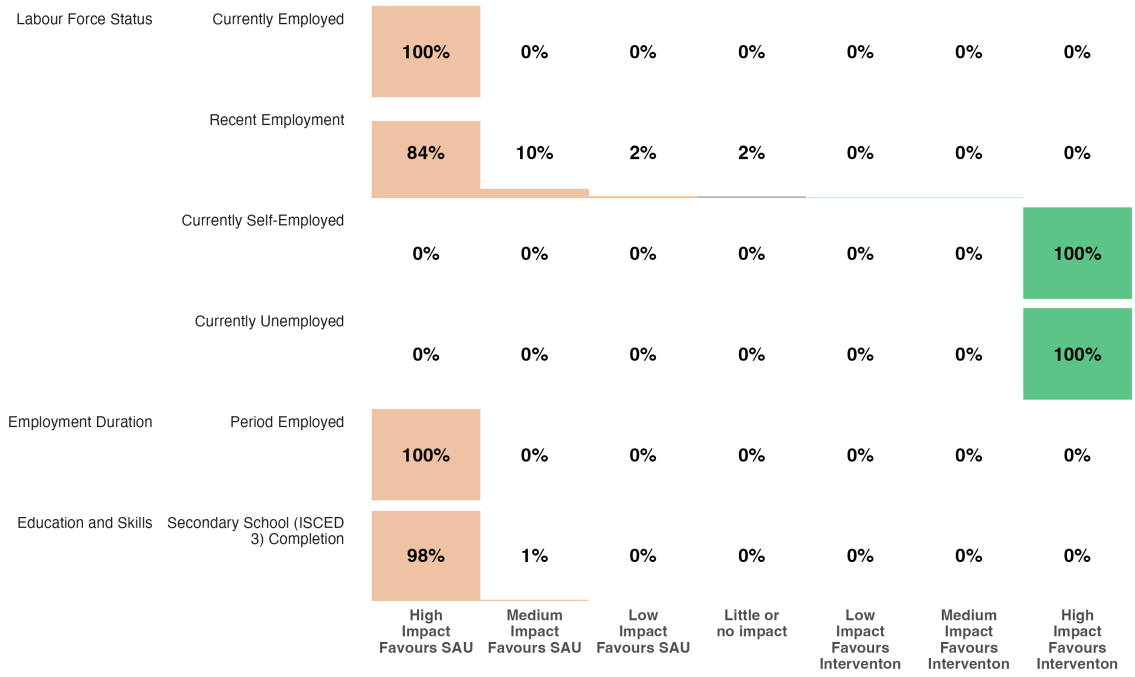
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 37 shows the posterior probability that the effect of Self-Employment Support on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 37 Probability of the scale of impact of Self-Employment Support

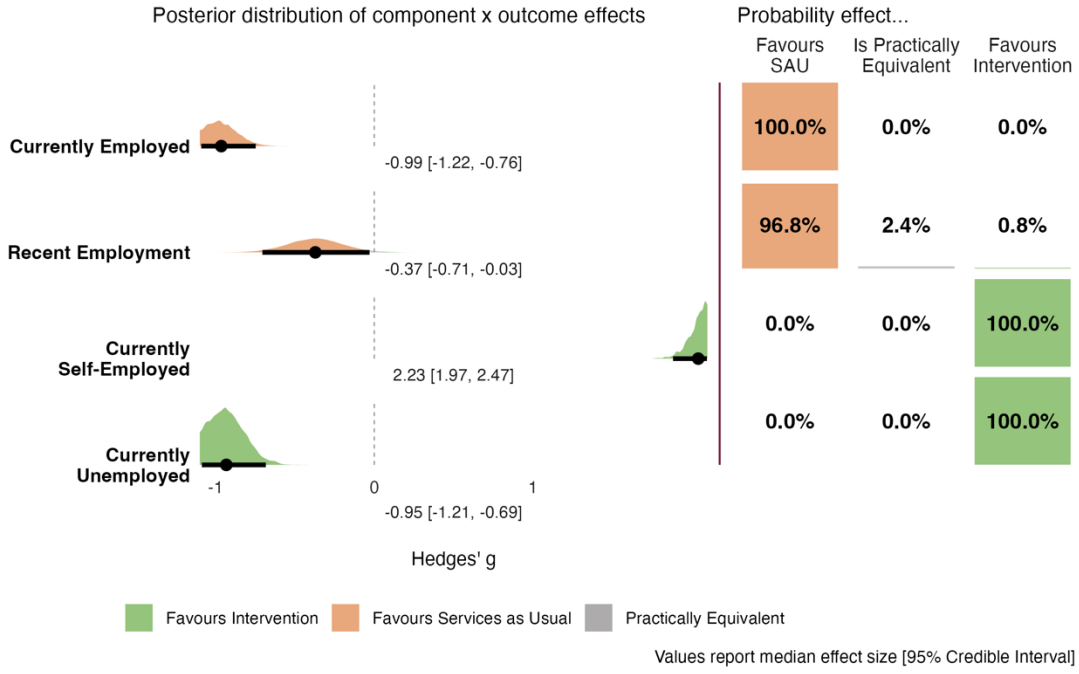


Labour Force status

The impact of Self-Employment Support on labour force outcomes is presented in Figure 38.

- Median estimates for Current Employment (*g*=-0.99) and Recent Employment (*g*=-0.37*)* show high negative impacts favouring SAU.
- In contrast, median estimates for Currently Self-Employed (*g*=2.23) and Currently Unemployed (*g*=-0.95) show high positive impacts favouring the intervention. The probability of a high impact in both outcomes is 100%. Although there were a small number of studies contributing to this finding, so effects should be interpreted with caution.
- Overall, these findings show preliminary evidence that Self-Employment Support can be very successful at current self-employment and reducing unemployment. Given the aims of the intervention is it perhaps not surprising that it appears to displace young people from being employed by others.

Figure 38 Impact of Self-Employment Support on Labour Force status

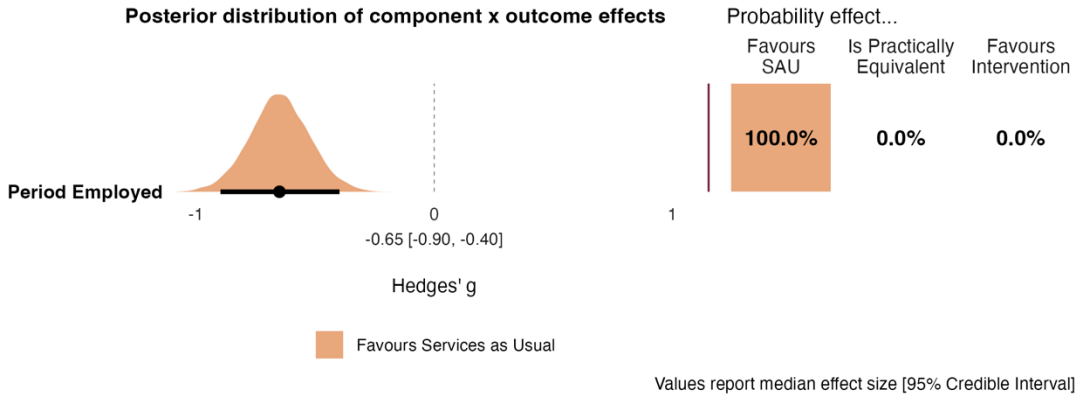


Employment duration

The impact of Self-Employment Support on employment duration outcomes is presented in Figure 39.

- The median estimate (*g*=-0.65) is high impact and favours SAU.
- The probability of a negative high impact is 100%.
- Consistent with the labour force status outcomes Self-Employment Support appears to reduce the period individuals are employed for.

Figure 39 Impact of Self-Employment Support on Employment duration

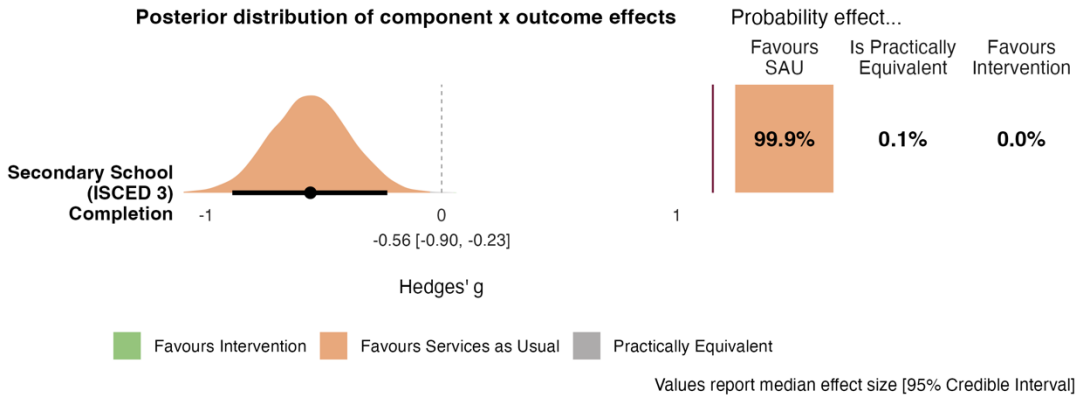


Education and Skills

The impact of Self-Employment Support on education and skills outcomes is presented in Figure 40.

- The median estimate for secondary school completion is a high impact negative outcome favouring SAU.
- The probability of a negative high impact is 100%.
- Consistent with the labour force and period worked outcomes Self-Employment Support appears to reduce probability of secondary school completion.

Figure 40 Impact of Self-Employment Support on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of self-employment support between females and males falls in the low effect range: *g*=-0.06, 95% CrI [-0.53, 0.41].
- **Posterior probabilities** — there is a 39.4% chance the impact of self-employment support is higher in all-female study populations and a 60.6% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=0.05 95% CrI [-0.11, 0.21] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.41, 95% CrI [-0.85, 1.67].
- **Posterior probabilities** — there is a 75.9% chance the impact of Self-Employment Support increases with the mean study age.

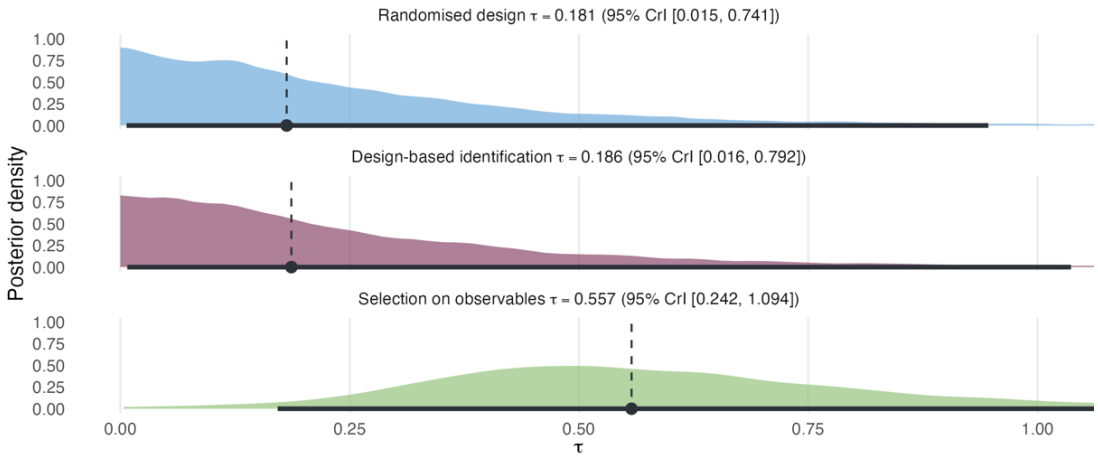
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 41 shows the component-specific heterogeneity by study design. Mirroring the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. However, the median and spread for all study designs is higher than the overall results. With only one RE and no DBI studies, we should interpret these cautiously. However, the median and spread of the SOO is much higher indicating considerable study design dependent variability for this component.

Figure 41 Posterior distribution of between study heterogeneity (τ) by for Self-Employment Support by study design





Employment Services

Meta-analysis results

Job Search Preparation

Key findings

- **Job Search Preparation had little or no effect in more than half of the assessed outcomes.** Three additional outcomes clearly favoured SAU.
- **Job Search Preparation has a positive impact on reducing NEET outcomes and time employed.** For Currently NEET, the median effect is high, with a high probability of an effect favouring the intervention (Pr > 0.05 = 0.85) and a substantial probability of a high-impact effect (Pr > 0.2 = 0.62). For Period Employed, there is a high probability of a positive effect (70%), though impacts are most likely to be low or medium in magnitude.
- **Impacts may vary by mean population age**. Effects appear similar between all-male and all-female study populations, but are more likely to increase as mean study age rises, with a medium-sized difference between studies with mean ages of 24 versus 16.
- **How to make sense of this.** Job Search Preparation is designed to influence labour market attachment Therefore, the greatest effect observed on reducing chances of being NEET with some signs of promise for increasing time in employment and increasing hours is intuitive. Further examination is required to understand more specifically how this component drives a reduction in NEET likelihood.

Definition

Job search preparation services focus on equipping young jobseekers with the tools and skills necessary to effectively navigate the job search process. These services may include workshops or one-on-one support for crafting professional resumes, cover letters, and online profiles that showcase the jobseeker's skills and experiences.

Evidence profile

A summary of the evidence used to inform the analysis of Job Search Preparation is summarised in Table 27. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 27 Evidence profile for Job Search Preparation

SUMMARY	COUNT			
Number of studies	65			
Number of effect sizes	202			
Study design	RE: 41	SOO: 21	DBI: 3	
Risk of bias	Acceptable: 41		High: 24	
Study design x risk of bias	Acceptable High	RE: 29 RE: 12	SOO: 9 SOO: 12	DBI: 3 DBI: 0
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=28); Recent Employment (n=14); Currently Unemployed (n=10); Currently NEET (n=5); Currently Not in the Labour Force (n=6)			
Employment Compensation	Labour Earnings (n=23); Wages (n=4)			
Employment duration	Period Employed (n=10)			
Hours Worked	Hours Worked (n=7)			
Education & Skills	Secondary School (ISCED 3) Participation (n=3); Secondary School (ISCED 3) Completion (n=21); Bachelors Degree (ISCED 6) Participation (n=10); Bachelors Degree (ISCED 6) Completion (n=4); Short-Cycle Tertiary (ISCED 5) Participation (n=4); Short-Cycle Tertiary (ISCED 5) Completion (n=4); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=3); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=1); Apprenticeship Participation (n=2); Occupational Licence Obtained (n=5)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Job Search Preparation. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

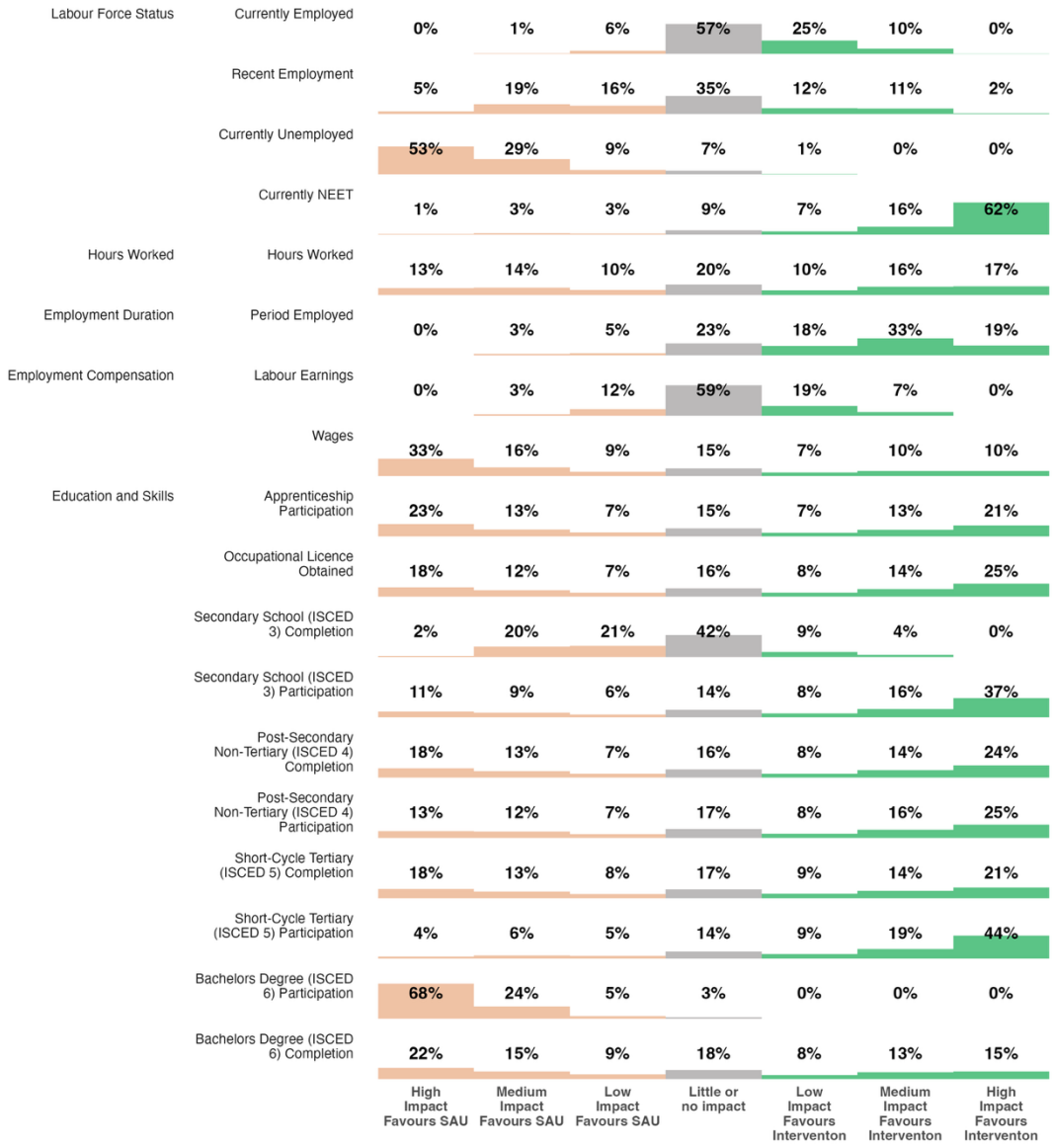
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 42 shows the posterior probability that the effect of Job Search Preparation on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 42 Probability of the scale of impact of Job Search Preparation



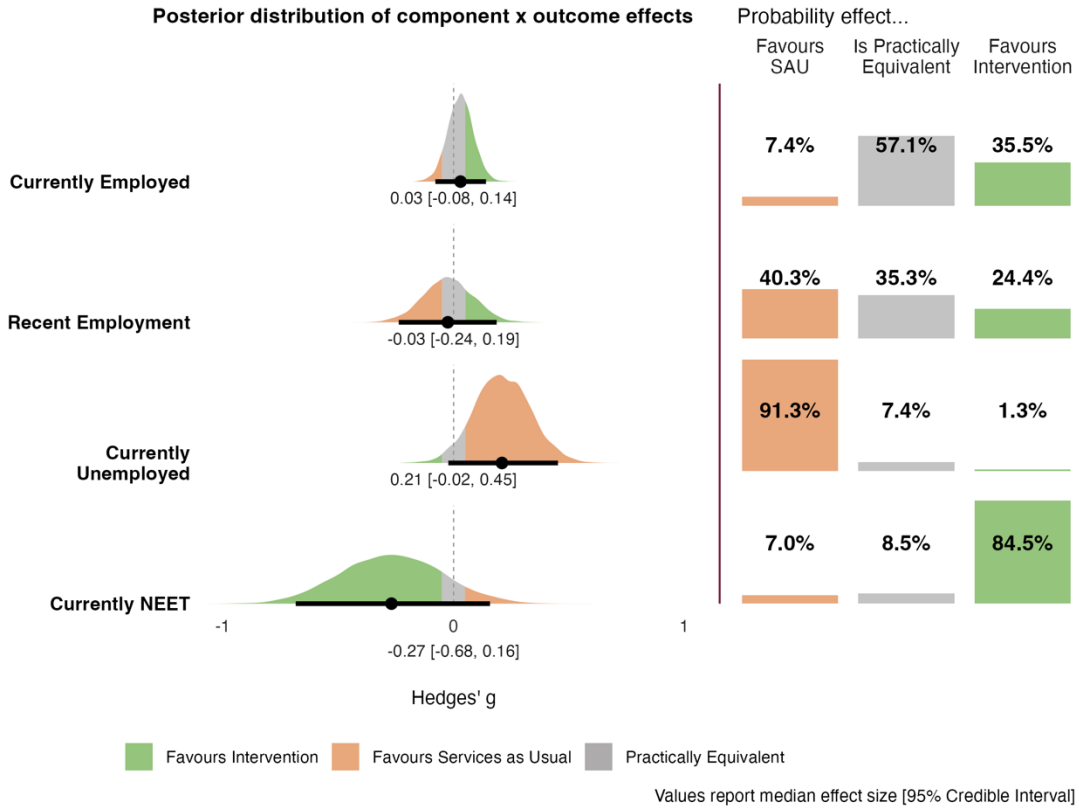
Labour Force status

The impact of Job Search Preparation on labour force outcomes is presented in Figure 43.

- Median estimates vary across the four outcomes. There is a high positive impact on Currently NEET and high impact in a negative direction for Currently Unemployed, There is little or no impact on Currently Employed and Recent Employment.

- The probability of an effect favouring Job Search Assistance is highest for Currently NEET (84.5%).
- The probability of a medium or high impact for Currently NEET is high (Pr > 0.1 = 0.78), but low elsewhere.
- Overall, these findings suggest that Job Search Preparation can have a positive impact on reducing NEET status, but its impact is otherwise inconclusive.

Figure 43 Impact of Job Search Preparation on Labour Force status



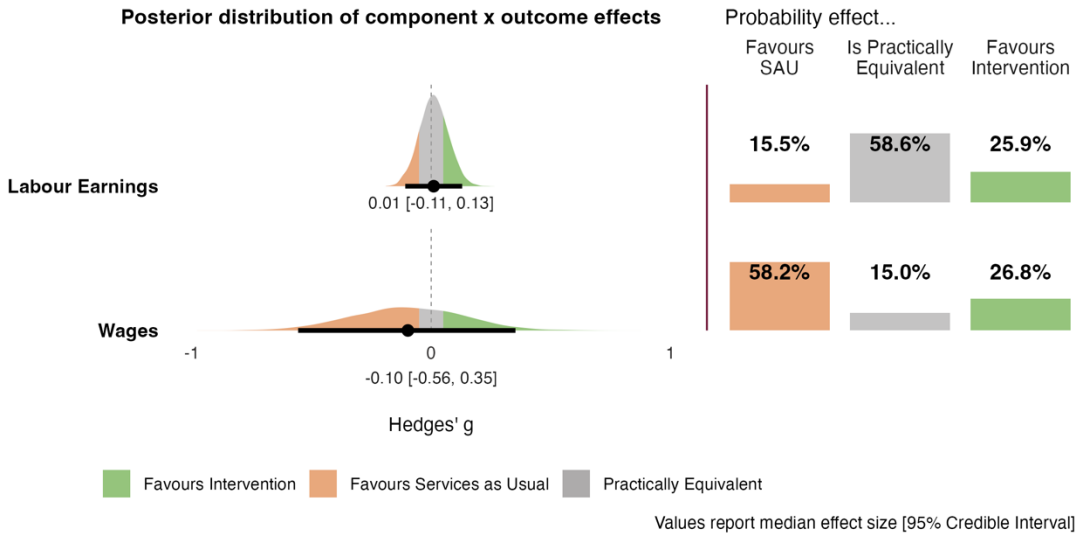
Employment compensation

The impact of Job Search Preparation on employment compensation outcomes is presented in Figure 44.

- The median estimates for the impact on Wages is low and favours SAU. There is little or no impact on Wages.
- There is a greater than even chance of an effect favouring SAU (Pr < 0.05 = 0.58) for Wages.

- The probability of medium or high positive impacts is very low across both outcomes.
- Overall, these results present little evidence that Job Search Preparation improves employment compensation, with effects most likely close to zero and unlikely to exceed the low impact range.

Figure 44 Impact of Job Search Preparation on Employment compensation

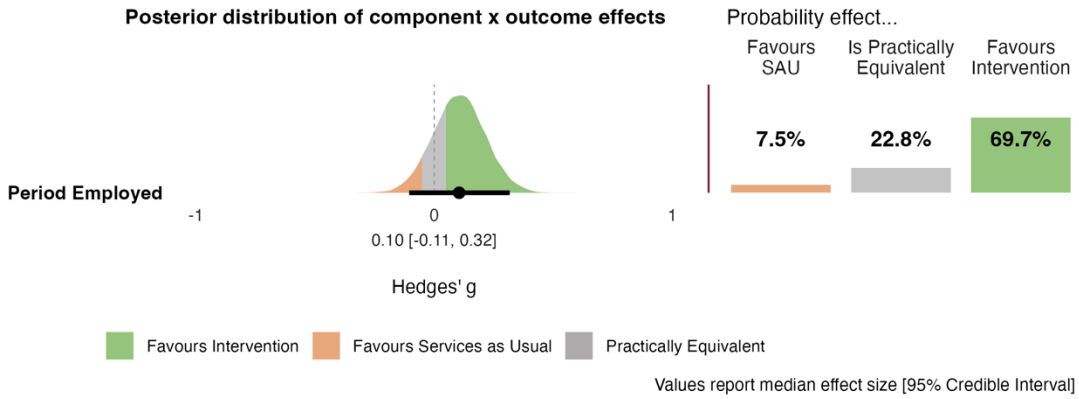


Employment duration

The impact of Job Search Preparation on employment duration outcomes is presented in Figure 45.

- Median estimate falls on the threshold of the medium impact range.
- The probability of any positive impact is 70%.
- The probability of a medium impact is moderate (33%), while a high impact is less likely (19%).
- Overall, Job Search Preparation may slightly increase time spent in employment.

Figure 45 Impact of Job Search Preparation on Employment duration

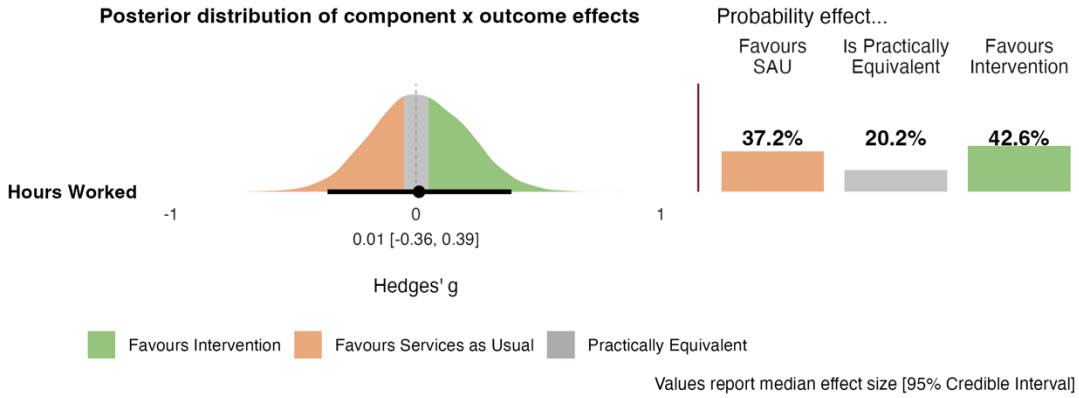


Hours worked

The impact of Job Search Preparation on Hours Worked is presented in Figure 46.

- The median estimate is near zero and falls within the little or no impact range.
- The probability of any positive impact is 43%.
- The probability of a medium (16%) or high (17%) impact is around 33%.
- Overall, Job Search Preparation has an inconclusive impact on Hours Worked.

Figure 46 Impact of Job Search Preparation on Hours worked

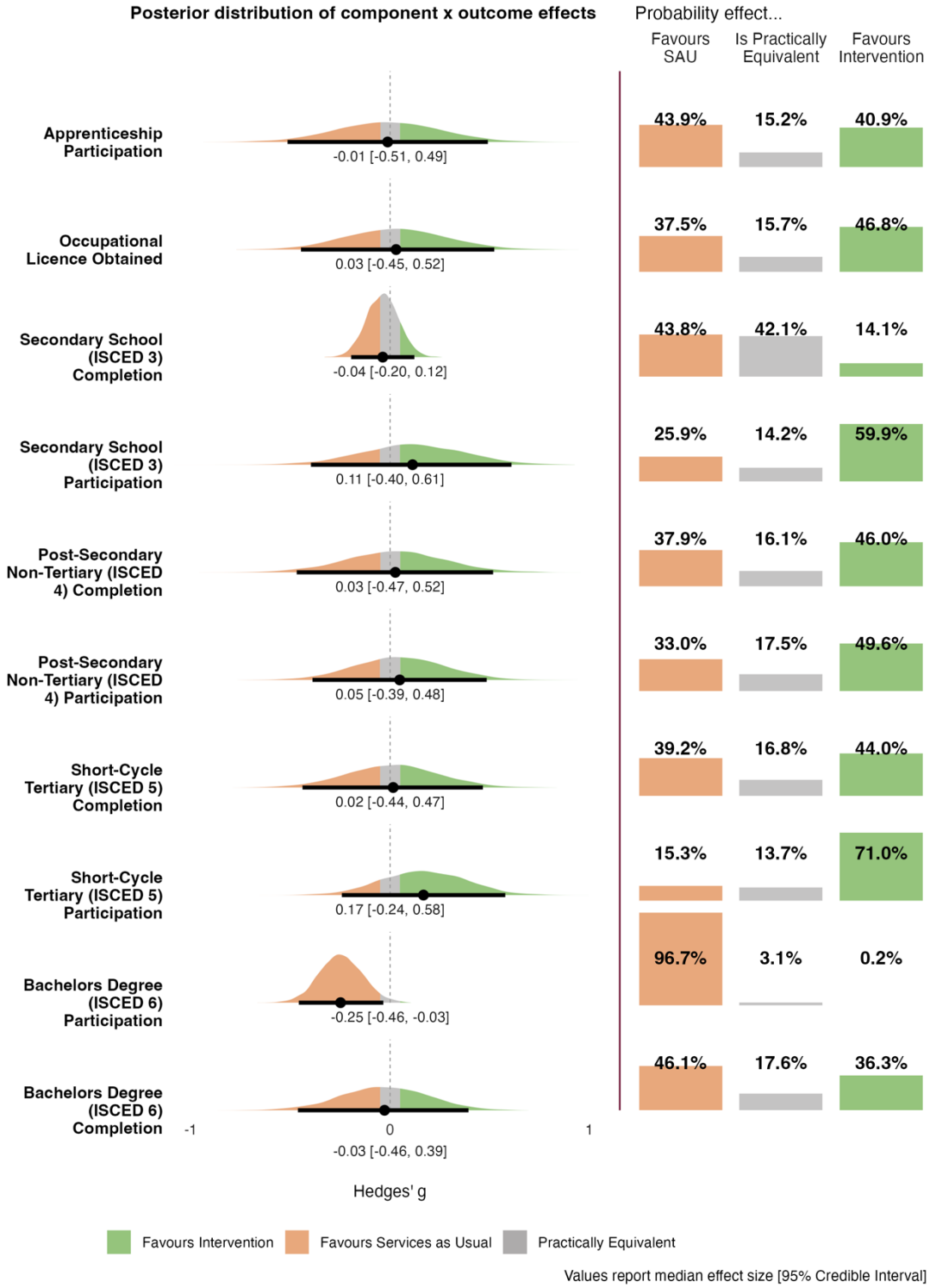


Education and Skills

The impact of Job Search Preparation on education and skills outcomes is presented in Figure 47. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls within the little or no impact range (g=-0.01).
- *Occupational licence attainment* — the median effect falls within the little or no impact range (*g*=0.03).
- *Secondary school completion* — the median effect falls within the little or no impact range (*g*=-0.04).
- *Bachelor's degree participation* — the median estimate falls in the high impact range (*g*=-0.22) and favours SAU.

Figure 47 Impact of Job Search Preparation on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of job search preparation between females and males falls in the range or low or no effect: *g*=0.00, 95% CrI [-0.08, 0.08].
- **Posterior probabilities** — there is a 49.3% chance the impact of job search preparation is higher in all-female study populations and a 50.7% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=-0.04 95% CrI [-0.09, 0.01] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.31, 95% CrI [-0.74, 0.09].
- **Posterior probabilities** — there is a 63.3% chance the impact of Job Search Preparation decreases with the mean study age.

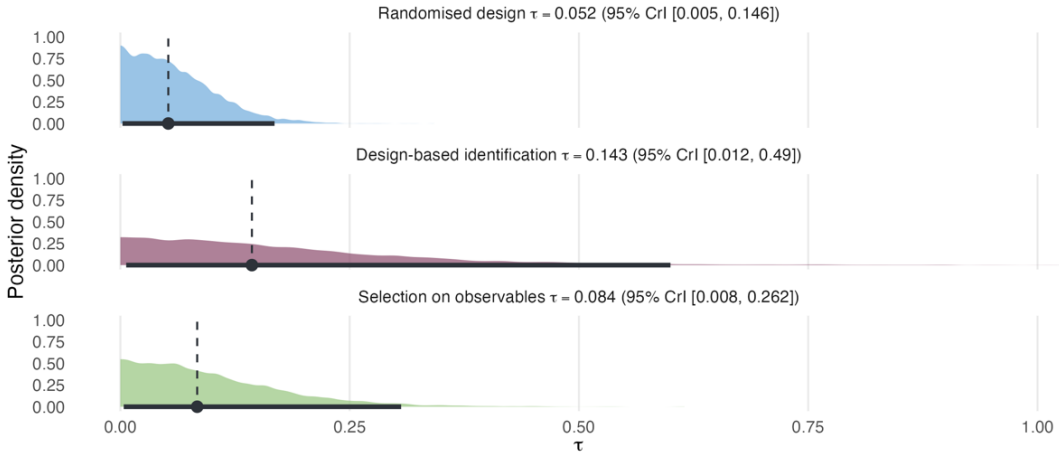
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 48 shows the component-specific heterogeneity by study design. Consistent with the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for each distribution is slightly lower than the overall results, however there is no meaningful change from the conclusion that SOO and DBI studies show greater variability.

Figure 48 Posterior distribution of between study heterogeneity (τ) by for Job Search Preparation by study design



Job Search Assistance

Key findings

- **Job Search Assistance has a positive impact on Wages.** There is a 67% probability of a positive effect and a 55% probability that the impact is at least medium-sized in magnitude.
- **The largest positive effect is on education and skills outcomes.** Median effects are very high for Bachelor's degree Participation (Pr > 0.05 = 0.99; Pr > 0.2 = 0.91), and Short-Cycle Tertiary Completion (Pr > 0.05 = 0.61; Pr > 0.1 = 0.35), and for Secondary School Participation (Pr > 0.05 = 0.61; Pr > 0.1 = 0.52).
- **Impacts vary by population**. Effects are likely (74%) to be larger in all-female study populations, with the difference being medium in magnitude. Effects are also likely to decrease as mean study age increases with a medium sized magnitude difference between a mean study age of 24 vs. 16.
- **How to make sense of this.** 70 studies were examined for this component so the evidence should be adequate to detect employment effects. It would warrant deeper investigation into intervention intent and design related to the impact on bachelor's degree participation. It may be that through the job search assistance young people had raised career ambitions that required higher levels of education as the immediate outcome ahead of longer-term labour market outcomes.

Definition

Job search assistance services provide targeted support to help young jobseekers identify and pursue suitable employment opportunities. These services may include access to job listings (either online or in-person, public or not-listed), job fairs, and employer networks, as well as personalised assistance in identifying job openings that align with the jobseeker's skills and interests.

Evidence profile

A summary of the evidence used to inform the analysis of Job Search Assistance is summarised in Table 28. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 28 Evidence profile for Job Search Assistance

SUMMARY	COUNT			
Number of studies	70			
Number of effect sizes	220			
Study design	RE: 40	SOO: 25	DBI: 5	
Risk of bias	Acceptable: 46		High: 24	
Study design x risk of bias	Acceptable High	RE: 28 RE: 12	SOO: 14 SOO: 11	DBI: 4 DBI: 1
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=29); Recent Employment (n=18); Currently Unemployed (n=8); Currently NEET (n=3); Currently Not in the Labour Force (n=4)			
Employment Compensation	Labour Earnings (n=27); Wages (n=6)			
Employment duration	Period Employed (n=13)			
Hours Worked	Hours Worked (n=9)			
Education & Skills	Secondary School (ISCED 3) Participation (n=11); Secondary School (ISCED 3) Completion (n=5); Bachelors Degree (ISCED 6) Participation (n=11); Bachelors Degree (ISCED 6) Completion (n=5); Short-Cycle Tertiary (ISCED 5) Participation (n=4); Short-Cycle Tertiary (ISCED 5) Completion (n=5); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=4); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=2); Apprenticeship Participation (n=3); Occupational Licence Obtained (n=6)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Job Search Assistance. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

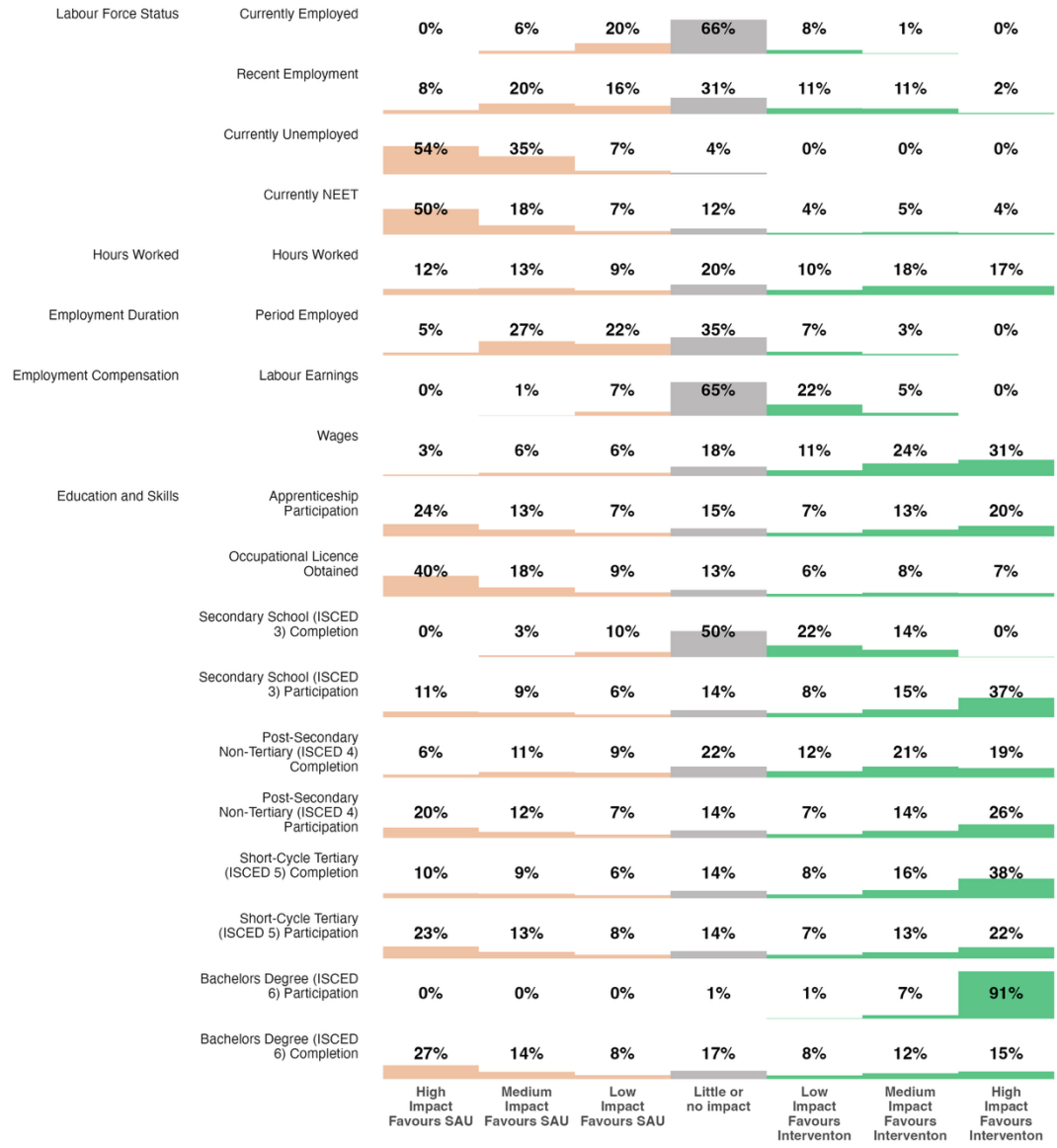
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 49 shows the posterior probability that the effect of Job Search Assistance on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 49 Probability of the scale of impact of Job Search Assistance

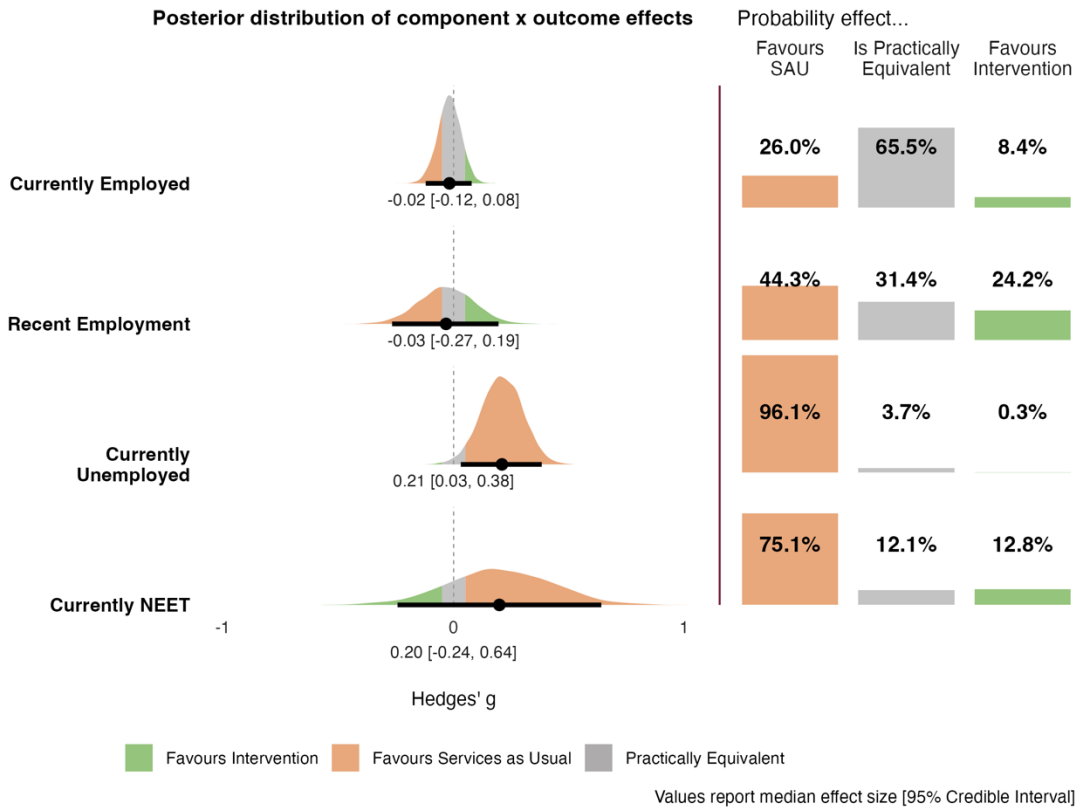


Labour Force status

The impact of Job Search Assistance on labour force outcomes is presented in Figure 50.

- Two median estimates—for Currently NEET and Currently Unemployed—are large negative effects favouring SAU. The results for Currently Employed and Recent Employment suggest Job Search Assistance has little or no effect relative to SAU.
- The probability of any impact favouring SAU s high for both Currently NEET and Currently Unemployed..
- Overall, these findings suggest that Job Search Assistance does not have an impact on labour force status.

Figure 50 Impact of Job Search Assistance on Labour Force status

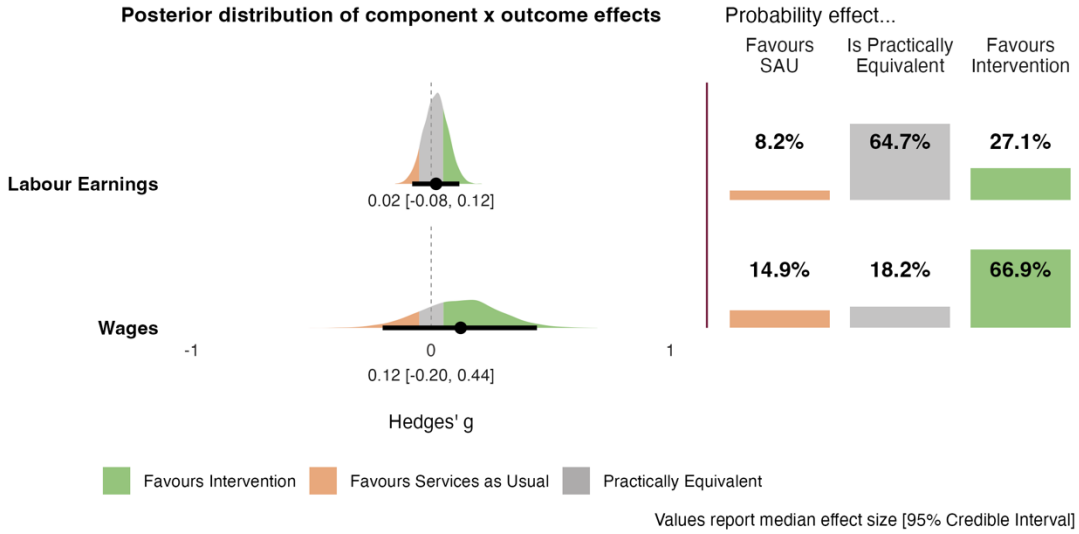


Employment compensation

The impact of Job Search Assistance on employment compensation outcomes is presented in Figure 51.

- The median estimate for Wages is a medium sized effect favouring Job Search Assistance. There is little or no effect on Labour Earnings.
- The probability of an impact favouring the internation is almost two-in-three (Pr > 0.05 = 0.7) for Wages. There is a more than even chance (Pr > 0.1 = 0.55) that the impact is medium or high in magnitude.
- Overall, these findings suggest that Job Search Assistance could have an impact on Wages.

Figure 51 Impact of Job Search Assistance on Employment compensation

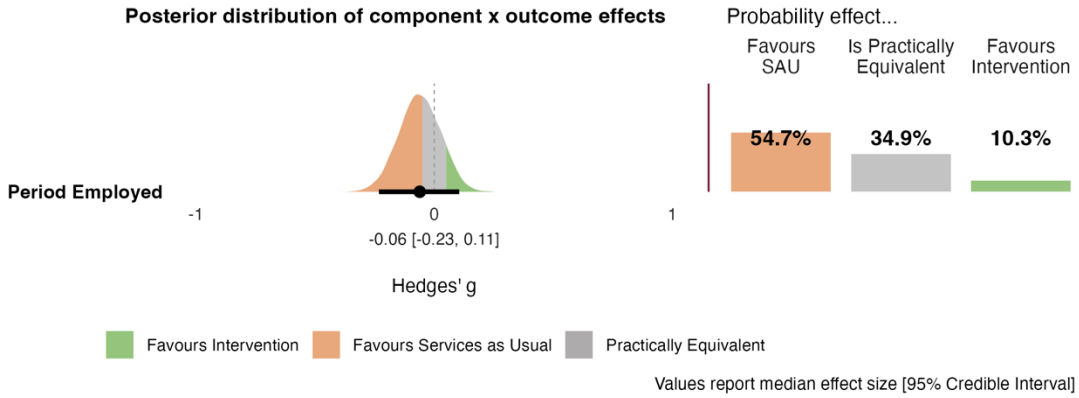


Employment duration

The impact of Job Search Assistance on employment duration outcomes is presented in Figure 52.

- The median estimate for Period Employed falls within the low impact range favouring SAU.
- The probability of any impact favouring SAU is 55%.
- Overall, Job Search Assistance does not appear to have an impact on employment duration.

Figure 52 Impact of Job Search Assistance on Employment duration

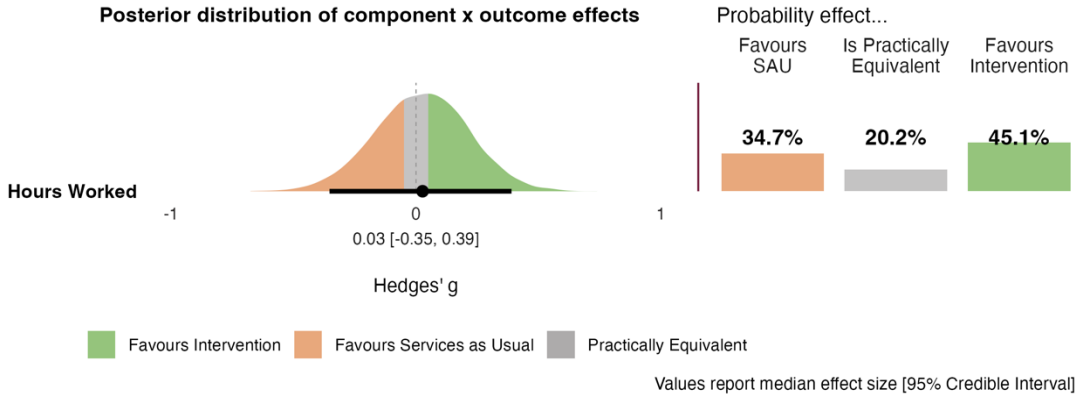


Hours worked

The impact of Job Search Assistance on hours worked is presented in Figure 53.

- The median estimate falls within the low impact range close to zero.
- The probability of any positive impact is 45%.
- The probability of a medium (18%) or high (17%) impact is less than 40%.
- Overall, Job Search Assistance has around a 50% chance of increasing hours worked.

Figure 53 Impact of Job Search Assistance on Hours worked



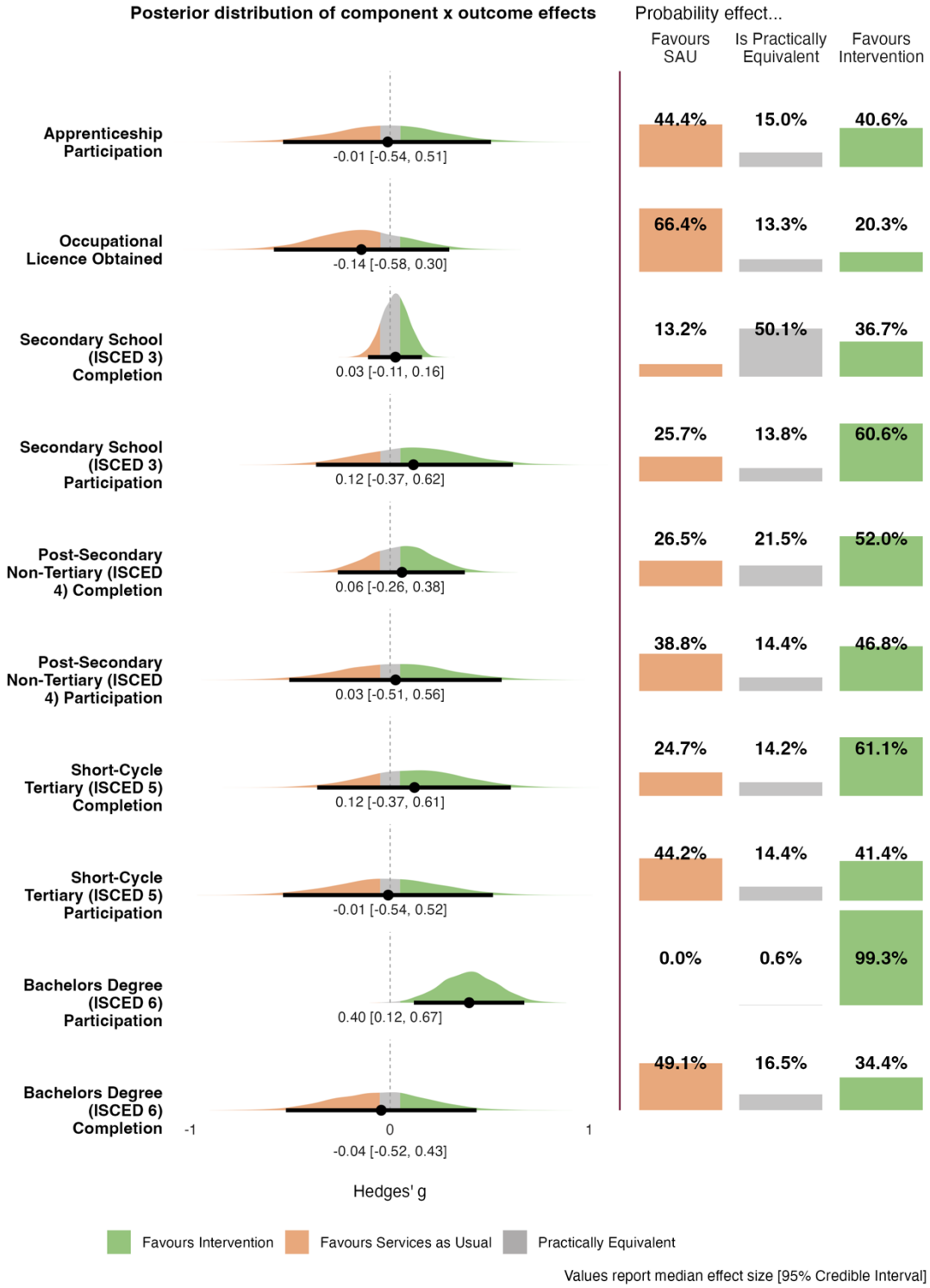
Education and Skills

The impact of Job Search Assistance on education and skills outcomes is presented in Figure 54. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls within the little or no impact range (g=-0.01).
- *Occupational licence attainment* — the median estimate falls in the medium impact range (g=-0.14) and favours SAU.
- *Secondary school completion* — the median effect falls within the range or little or no effect (*g*=0.03).
- *Bachelor's degree participation* — the median estimate falls in the high impact range (*g*=0.40). The probability of a positive impact favouring the intervention is almost certain (99%); and it is very likely to be high (91%) in magnitude.

Overall, while most education outcomes are likely to be low or uncertain, the results suggest Job Search Assistance may meaningfully increase bachelor's degree participation.

Figure 54 Impact of Job Search Assistance on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of job search assistance between females and males falls within the range of little or no effect: *g*=0.02, 95% CrI [-0.07, 0.04].
- **Posterior probabilities** — there is a 74.3% chance the impact of job search assistance is higher in all-female study populations and a 25.7% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=0.01, 95% CrI [-0.02, 0.05] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.11, 95% CrI [-0.18, 0.39].

- **Posterior probabilities** — there is a 77.5% chance the impact of Job Search Assistance increases with the mean study age.

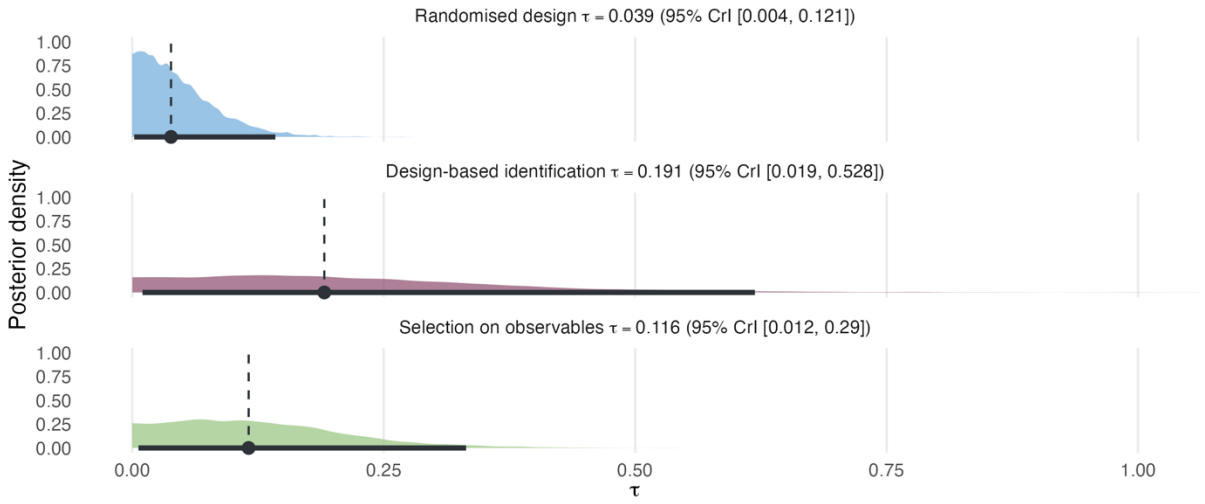
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 55 shows the component-specific heterogeneity by study design. As in the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. Although, the median and spread for RE and SOO is lower than the overall pattern, there is no meaningful change from the conclusion that SOO and DBI studies show greater variability.

Figure 55 Posterior distribution of between study heterogeneity (τ) by for Job Search Assistance by study design



Employment Counselling

Key findings

- **Employment Counselling may reduce current unemployment and increase time in employment.** Medium sized effects are observed for Currently Unemployed (Pr > 0.05 = 0.67; Pr > 0.1 = 0.67), and Period Employed (Pr > 0.05 = 0.77; Pr > 0.1 = 0.60), indicating a reasonable likelihood that impacts favour the intervention and are at least medium in magnitude.
- **Positive impacts on Bachelor's degree Participation**. There is a high (73%) probability of a positive impact on bachelor's degree Participation, and a greater than even chance (57%) that the impact is at least medium-sized in magnitude.
- **Impacts vary by population characteristics.** Effects are likely to be larger in all-male study populations (89%), though differences are small in magnitude. Effects are also more likely to increase with mean study age, with a medium-sized difference between studies with mean ages of 24 versus 16.
- **How to make sense of this.** Effects on unemployment and employment duration are consistent with the intent of employment counselling, while positive effects on bachelor's degree participation are less directly targeted and may reflect raised career aspirations or increased engagement with higher-level training pathways. Further investigation of programme design and participant pathways would help clarify the mechanisms through which programmes have these effects.

Definition

Employment counselling offers guidance to help jobseekers to assess their skills and interests, and explore suitable employment options. These services may include one-on-one sessions with trained counsellors who help jobseekers understand the labour market, identify potential career paths, and develop a plan to pursue their desired employment outcomes.

Evidence profile

A summary of the evidence used to inform the analysis of Employment Counselling is summarised in Table 29. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 29 Evidence profile for Employment Counselling

SUMMARY	COUNT			
Number of studies	90			
Number of effect sizes	261			
Study design	RE: 49	SOO: 32	DBI: 9	
Risk of bias	Acceptable: 54		High: 36	
Study design x risk of bias	Acceptable High	RE: 34 RE: 15	SOO: 15 SOO: 17	DBI: 5 DBI: 4
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=48); Recent Employment (n=16); Currently Unemployed (n=10); Currently NEET (n=7); Currently Not in the Labour Force (n=6)			
Employment Compensation	Labour Earnings (n=34); Wages (n=8)			
Employment duration	Period Employed (n=12)			
Hours Worked	Hours Worked (n=12)			
Education & Skills	Secondary School (ISCED 3) Participation (n=4); Secondary School (ISCED 3) Completion (n=27); Bachelors Degree (ISCED 6) Participation (n=10); Bachelors Degree (ISCED 6) Completion (n=6); Short-Cycle Tertiary (ISCED 5) Participation (n=3); Short-Cycle Tertiary (ISCED 5) Completion (n=4); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=2); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=1); Apprenticeship Participation (n=3); Occupational Licence Obtained (n=4)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Employment Counselling. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

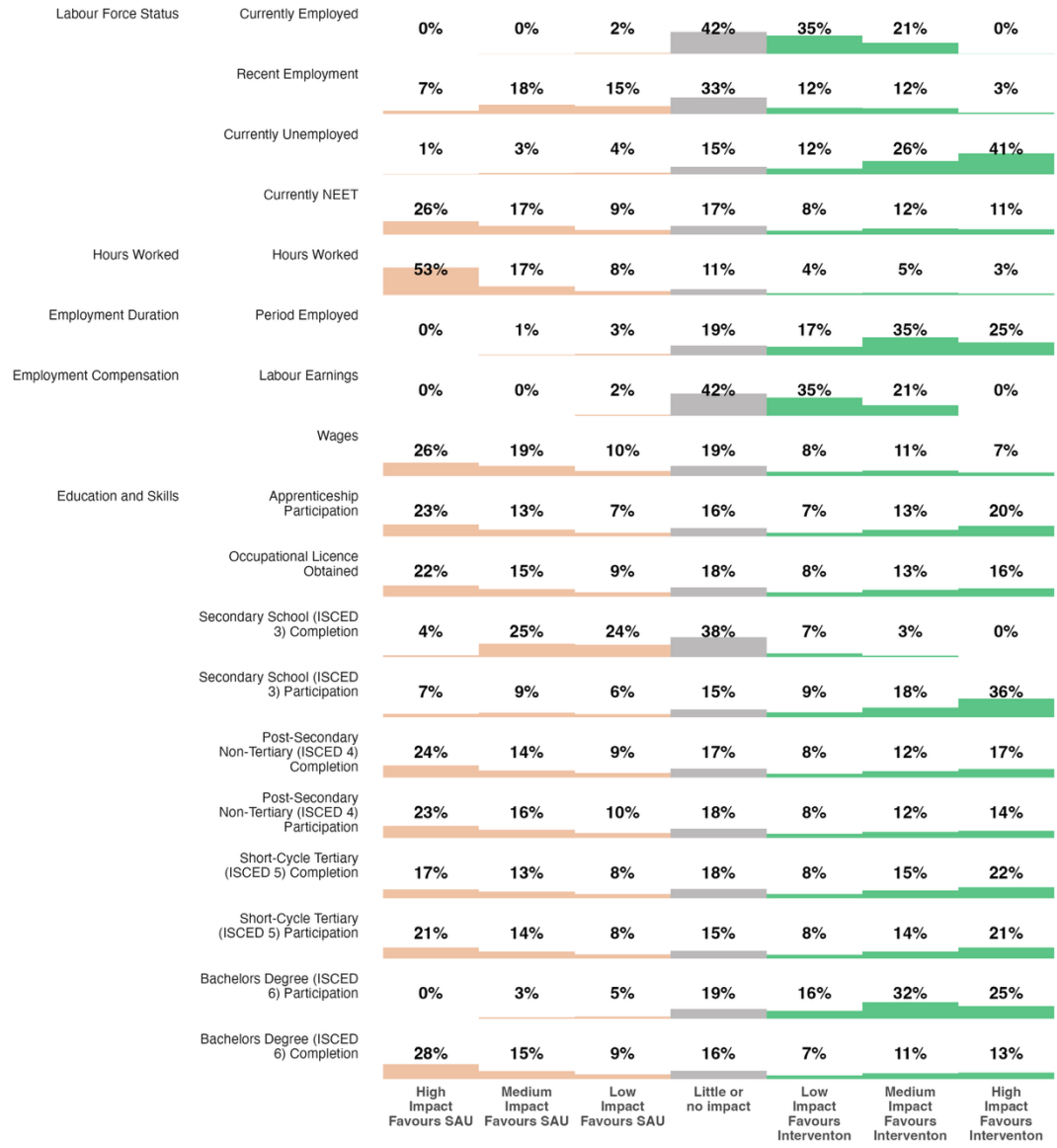
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 56 shows the posterior probability that the effect of Employment Counselling on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 56 Probability of the scale of impact of Employment Counselling



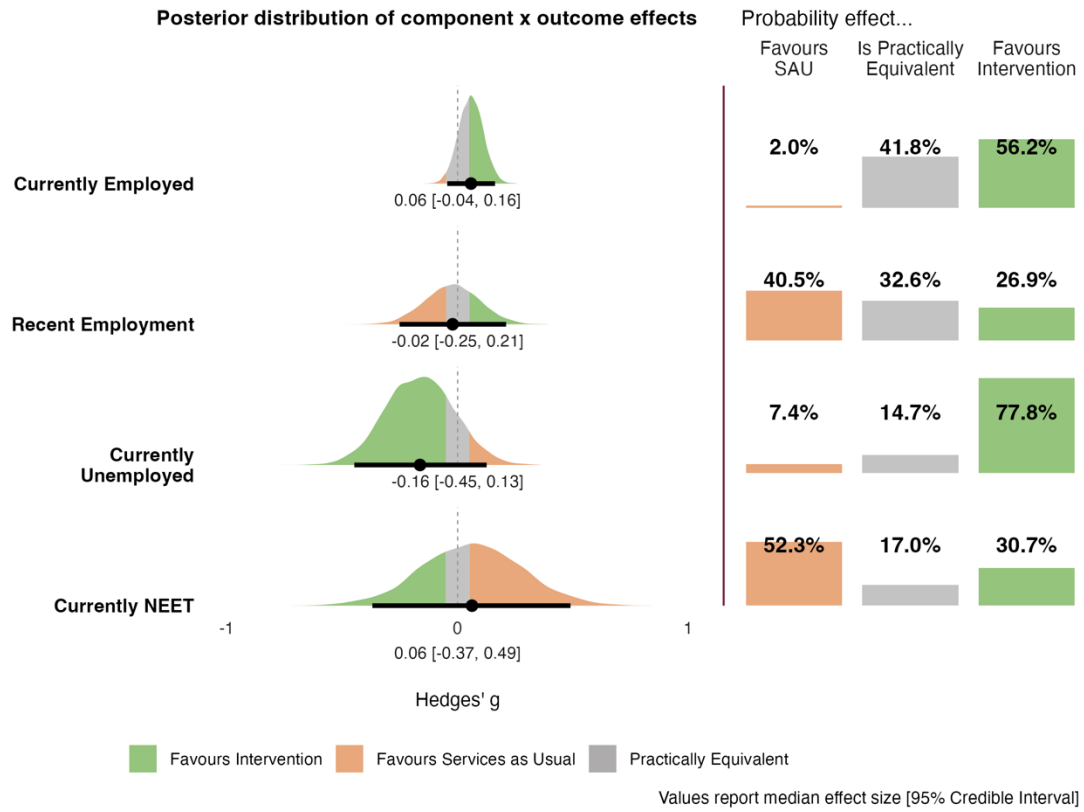
Labour Force status

The impact of Employment Counselling on labour force outcomes is presented in Figure 57.

- Median estimates mostly favour the intervention, however their magnitude varies. A medium-sized reduction in Currently Unemployed, a low reduction in Currently Unemployed and a low increase in Currently Employed all favour the Employment Counselling. Little or no impact is observed for Recent Employment.

- The probability of any positive impact is highest for Currently Unemployed (78%), followed by Currently Employed (56%).
- The probability of a medium or high impact is highest for Currently Unemployed (67%), and substantially lower (21%) for Currently Employed.
- Overall, these findings suggest that Employment Counselling can have an impact on reducing unemployment and to a much lessor extent increasing employment.

Figure 57 Impact of Employment Counselling on Labour Force status

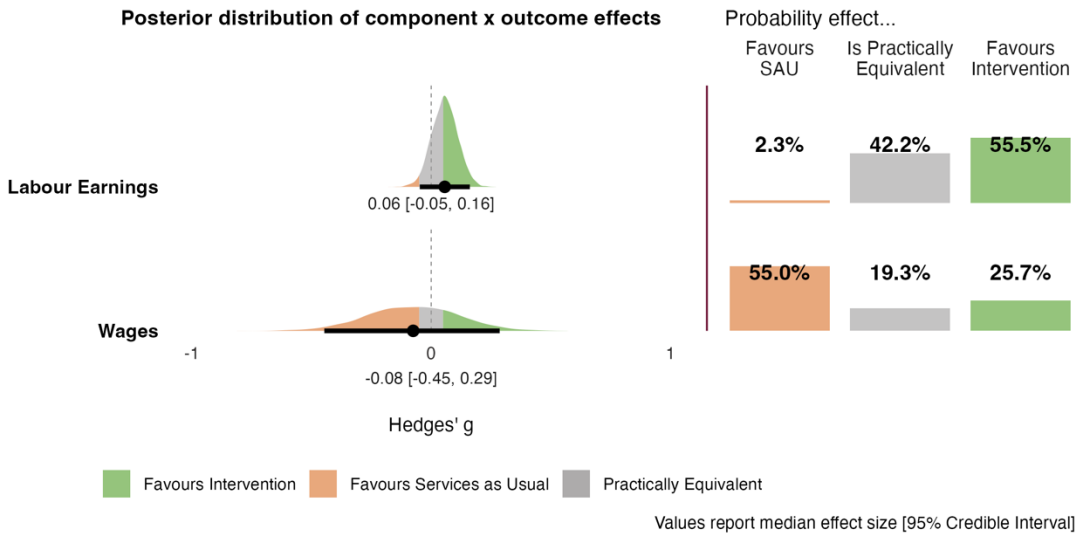


Employment compensation

The impact of Employment Counselling on employment compensation outcomes is presented in Figure 58.

- Median estimates for both labour earnings and wages both fall within the low impact range, with the median effect for wages favouring SAU.
- The probability of a positive impact favouring the intervention is roughly even (56%) for Labour Earnings.
- The probability of medium or high impacts is low for both outcomes (~20%).
- Overall, these results suggest that Employment Counselling can increase Labour Earnings, but the impact is most likely to be low.

Figure 58 Impact of Employment Counselling on Employment compensation



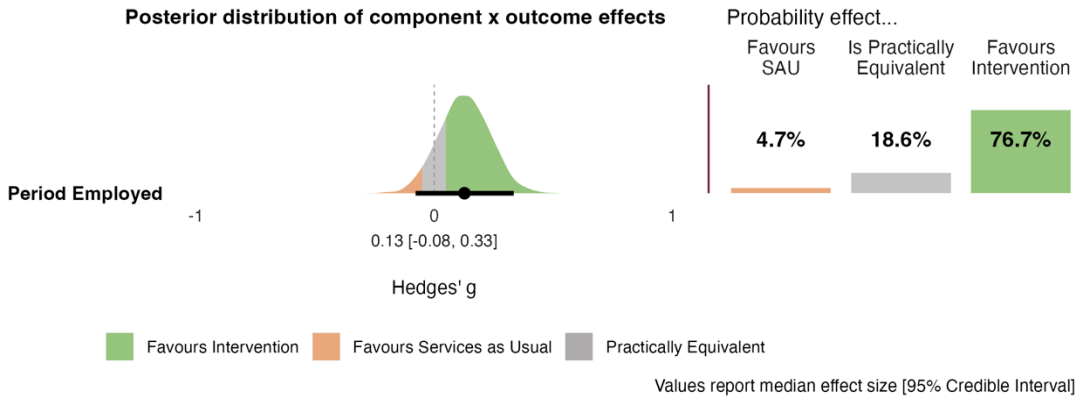
Employment duration

The impact of Employment Counselling on employment duration outcomes is presented in Figure 59.

- The median estimate for Period Employed favours the intervention and falls within the medium impact range.
- The probability of any positive impact is 77%. The probability of a medium (35%) and high (25%) is approximately 60%.

- Overall, Employment Counselling appears to increase time spent in employment.

Figure 59 Impact of Employment Counselling on Employment duration

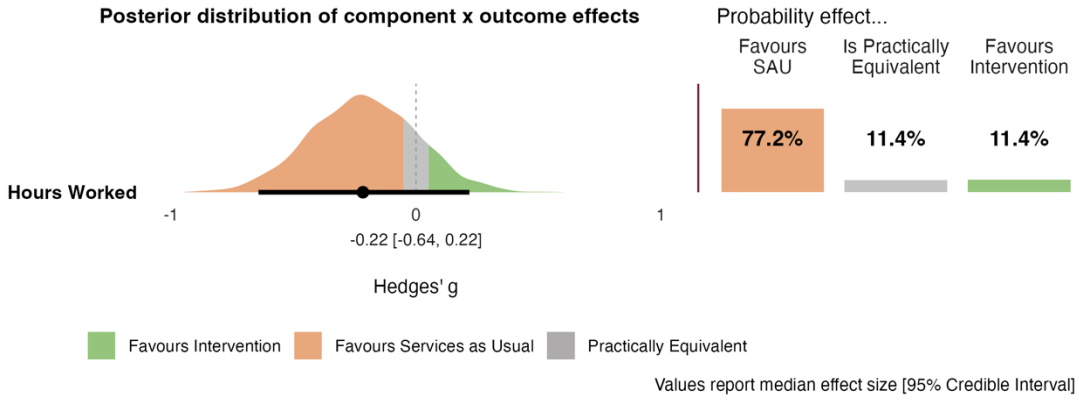


Hours worked

The impact of Employment Counselling on Hours Worked is presented in Figure 60.

- The median estimate is a high impact favouring SAU.
- The probability of an impact favouring SAU is high (Pr < 0.05 = 0.77).
- Overall, Employment Counselling does not appear to increase hours worked.

Figure 60 Impact of Employment Counselling on Hours worked



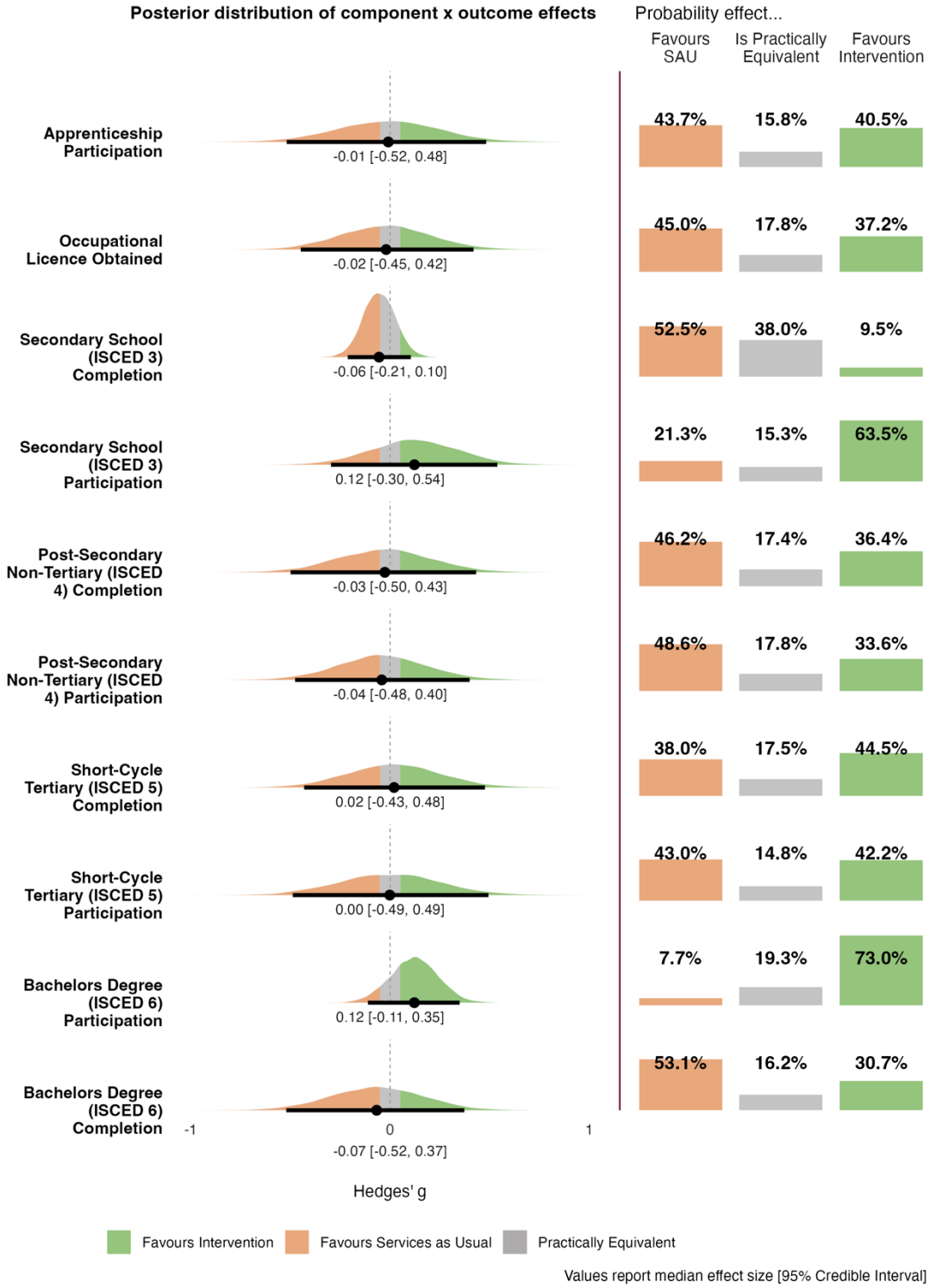
Education and Skills

The impact of Employment Counselling on education and skills outcomes is presented in Figure 61. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls within the little or no impact range (g=-0.01).
- *Occupational licence attainment* — the median estimate falls within the little or no impact range (g=-0.02).
- *Secondary school completion* — the median effect falls within the low impact range (*g*=-0.06) and favours SAU.
- *Bachelor's degree participation* — the median estimate falls in the medium impact range (*g*=0.12). The probability of a positive impact favouring the intervention is high (73%); and there is a more than even chance (57%) that the magnitude is medium or high.

Overall, while most education outcomes are likely to be low or uncertain, the results suggest Employment Counselling may increase bachelor's degree participation

Figure 61 Impact of Employment Counselling on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of employment counselling between females and males falls within the bound of little or no effect: *g*=-0.03, 95% CrI [-0.07, 0.02].
- **Posterior probabilities** — there is an 11.3% chance the impact of employment counselling is higher in all-female study populations and an 88.6% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=0.02 95% CrI [-0.07, 0.17] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.16, 95% CrI [-0.17, 0.54].

- **Posterior probabilities** — there is an 83.3% chance the impact of Employment Counselling increases with the mean study age.

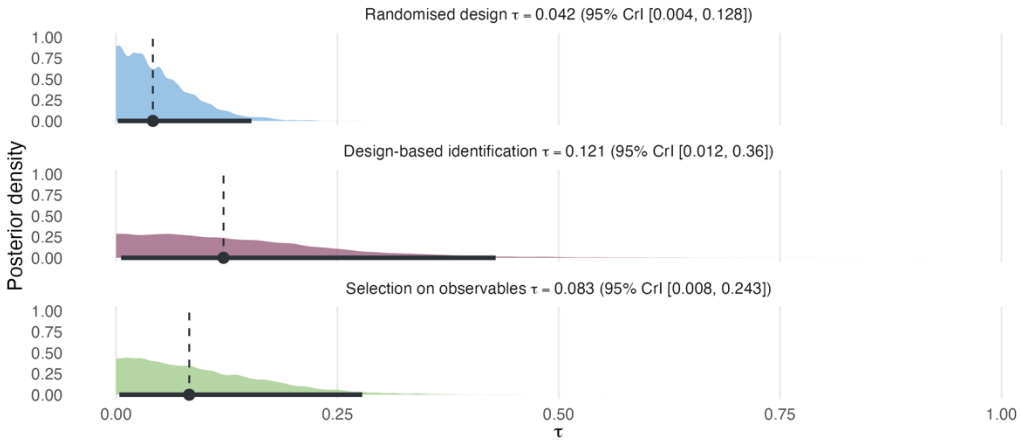
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 62 shows the component-specific heterogeneity by study design. As in the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for each distribution is lower the overall results, however there is no meaningful change from the conclusion that SOO and DBI studies show greater variability.

Figure 62 Posterior distribution of between study heterogeneity (τ) by for Employment Counselling by study design



Employment Coaching

Key findings

- **Employment Coaching reduces NEET rates.** Median effects are very high for Currently NEET (Pr > 0.05 = 0.96; Pr > 0.1 = 0.93), indicating a high likelihood that impacts favour the intervention and are at least medium in magnitude.
- **Impacts vary by population**. Effects may be (77%) larger in all-female study populations, however the difference is within the magnitude of little or no effect. Effects are also likely to decrease as mean study age increases, but the magnitude of difference between a mean study age of 24 vs. 16 is within the range of little or no effect.
- **How to make sense of this.** The commonality of findings between Job Search Assistance, Employment Counselling and Employment Coaching suggests some further investigation is required. It may be that those interventions that report higher education (bachelor's degree participation) outcomes share a focus on raising ambitions or it may reflect differences in the characteristics of participants.

Definition

Employment coaching services provide access to guidance and support during the application and selection process. These services may include interview preparation, coaching on workplace communication and etiquette, and guidance on navigating the challenges of starting a new job.

Evidence profile

A summary of the evidence used to inform the analysis of Employment Coaching is summarised in Table 30. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 30 Evidence profile for Employment Coaching

SUMMARY	COUNT			
Number of studies	77			
Number of effect sizes	232			
Study design	RE: 45	SOO: 27	DBI: 5	
Risk of bias	Acceptable: 41		High: 36	
Study design x risk of bias	Acceptable High	RE: 28 RE: 17	SOO: 10 SOO: 17	DBI: 3 DBI: 2
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=42); Recent Employment (n=16); Currently Unemployed (n=10); Currently NEET (n=9); Currently Not in the Labour Force (n=7)			
Employment Compensation	Labour Earnings (n=27); Wages (n=8)			
Employment duration	Period Employed (n=11)			
Hours Worked	Hours Worked (n=14)			
Education & Skills	Secondary School (ISCED 3) Participation (n=2); Secondary School (ISCED 3) Completion (n=11); Bachelors Degree (ISCED 6) Participation (n=11); Bachelors Degree (ISCED 6) Completion (n=2); Short-Cycle Tertiary (ISCED 5) Participation (n=5); Short-Cycle Tertiary (ISCED 5) Completion (n=28); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=2); Apprenticeship Participation (n=2); Occupational Licence Obtained (n=4)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Employment Coaching. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 63 shows the posterior probability that the effect of Employment Coaching on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 63 Probability of the scale of impact of Employment Coaching



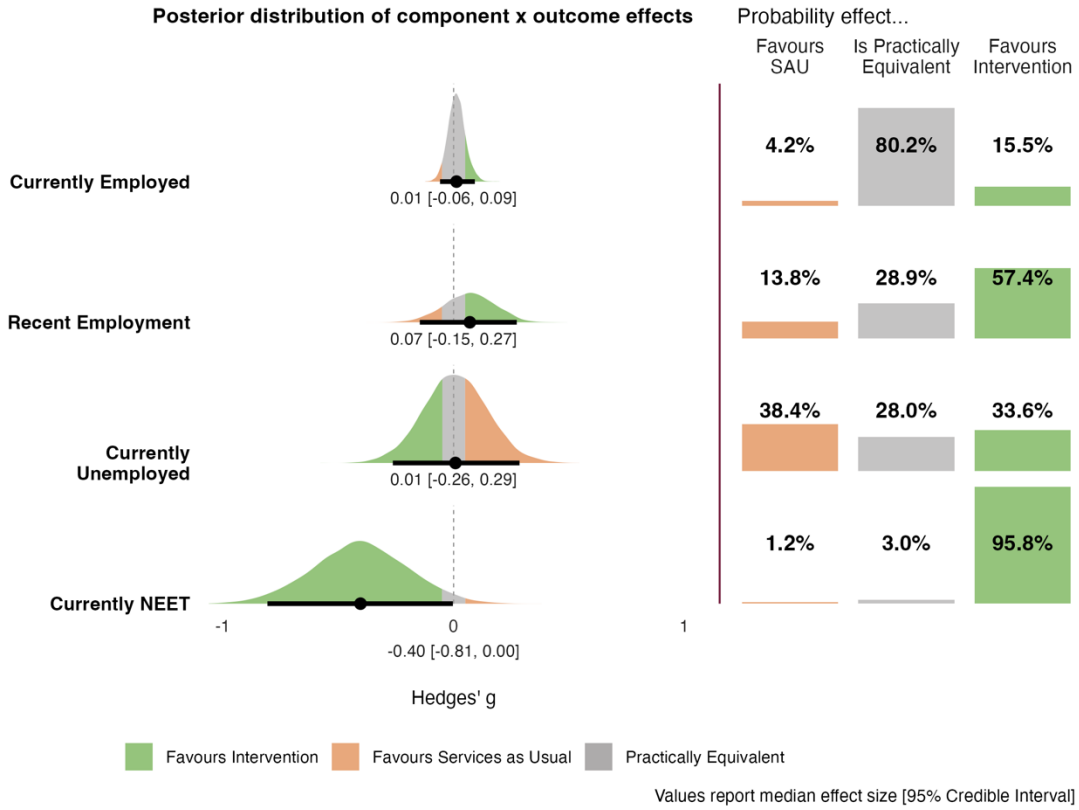
Labour Force status

The impact of Employment Coaching on labour force outcomes is presented in Figure 64.

- The median estimates for Currently NEET shows a high magnitude effect favouring the intervention. Recent employment also favours the intervention, however the magnitude is low. Median estimates for Currently Employed and Currently Unemployed indicate little or no effect.

- The probability of any positive impact for Currently NEET is almost very high (Pr > 0.05 = 96).
- The probability of a medium (9%) or high (84%) impact is very high (93%) for Currently NEET.
- Overall, these findings suggest that Employment Coaching has the very high probability reducing NEET status.

Figure 64 Impact of Employment Coaching on Labour Force status



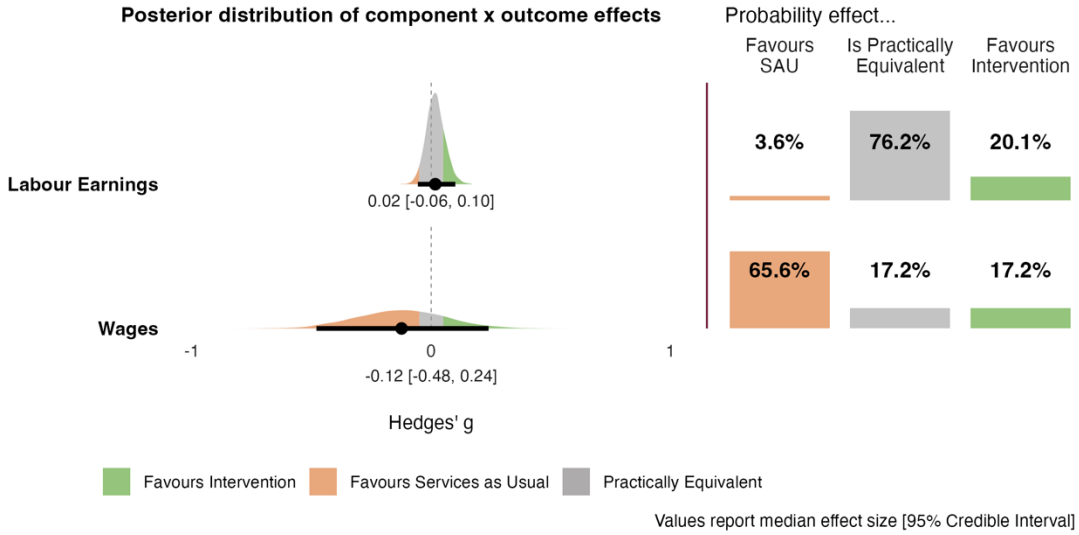
Employment compensation

The impact of Employment Coaching on employment compensation outcomes is presented in Figure 65.

- The median estimates for Labour Earnings indicates little or no effect. Whereas there is a medium-sized negative effect favouring SAU for wages.
- The probability of any positive impact is low for both outcomes: 17% for wages and 20% for labour earnings.

- The probability of medium or high impacts is very low across both outcomes (<5%).
- Overall, these results suggest that Employment Coaching may increase Labour Earnings, but its impact is likely to be low.

Figure 65 Impact of Employment Coaching on Employment compensation

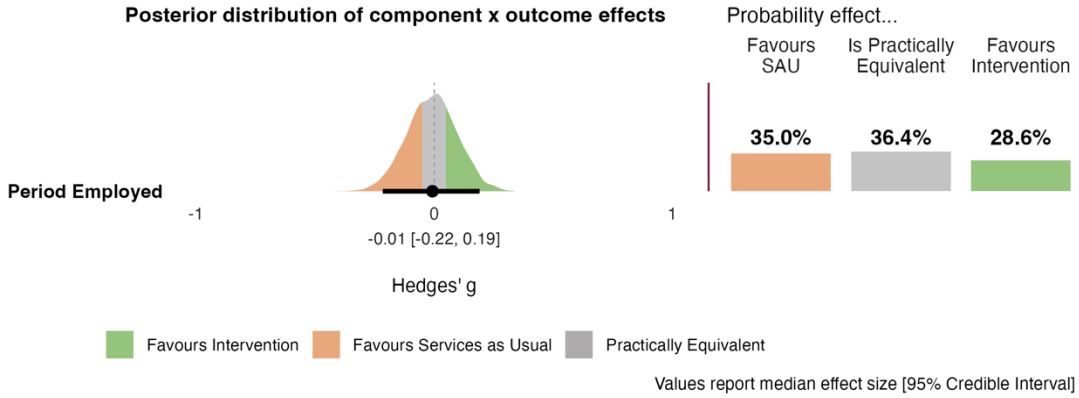


Employment duration

The impact of Employment Coaching on employment duration outcomes is presented in Figure 66.

- The median estimate indicates little or no effect on Period Employed.
- The probability of any positive impact is 29%.
- The probability of a medium impact is modest (13%), while a high impact is very unlikely (2%).
- Overall, Employment Coaching does not appear to change time spent in employment.

Figure 66 Impact of Employment Coaching on Employment duration

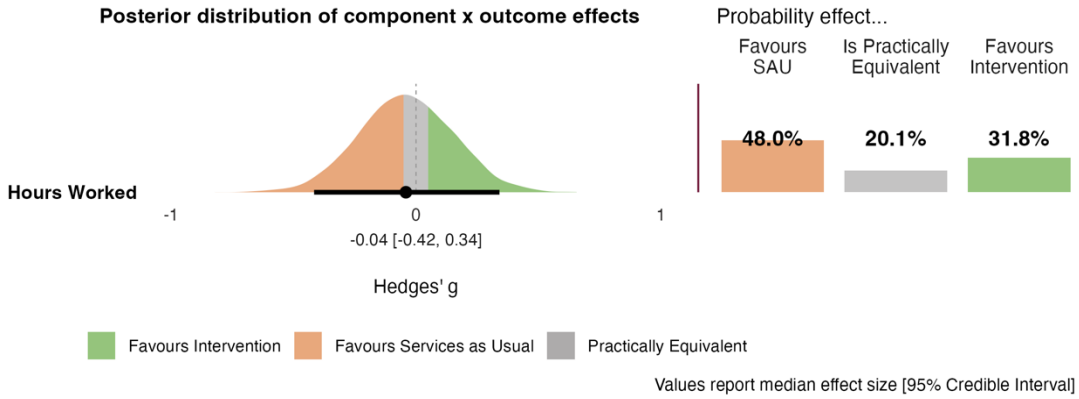


Hours worked

The impact of Employment Coaching on hours worked is presented in Figure 67.

- The median estimate falls within the range of little or no effect.
- The probability of any positive impact is 32%.
- The probability of a medium (13%) or high (11%) impact is less that <25%.
- Overall, Employment Coaching does not appear to increase hours worked.

Figure 67 Impact of Employment Coaching on Hours worked



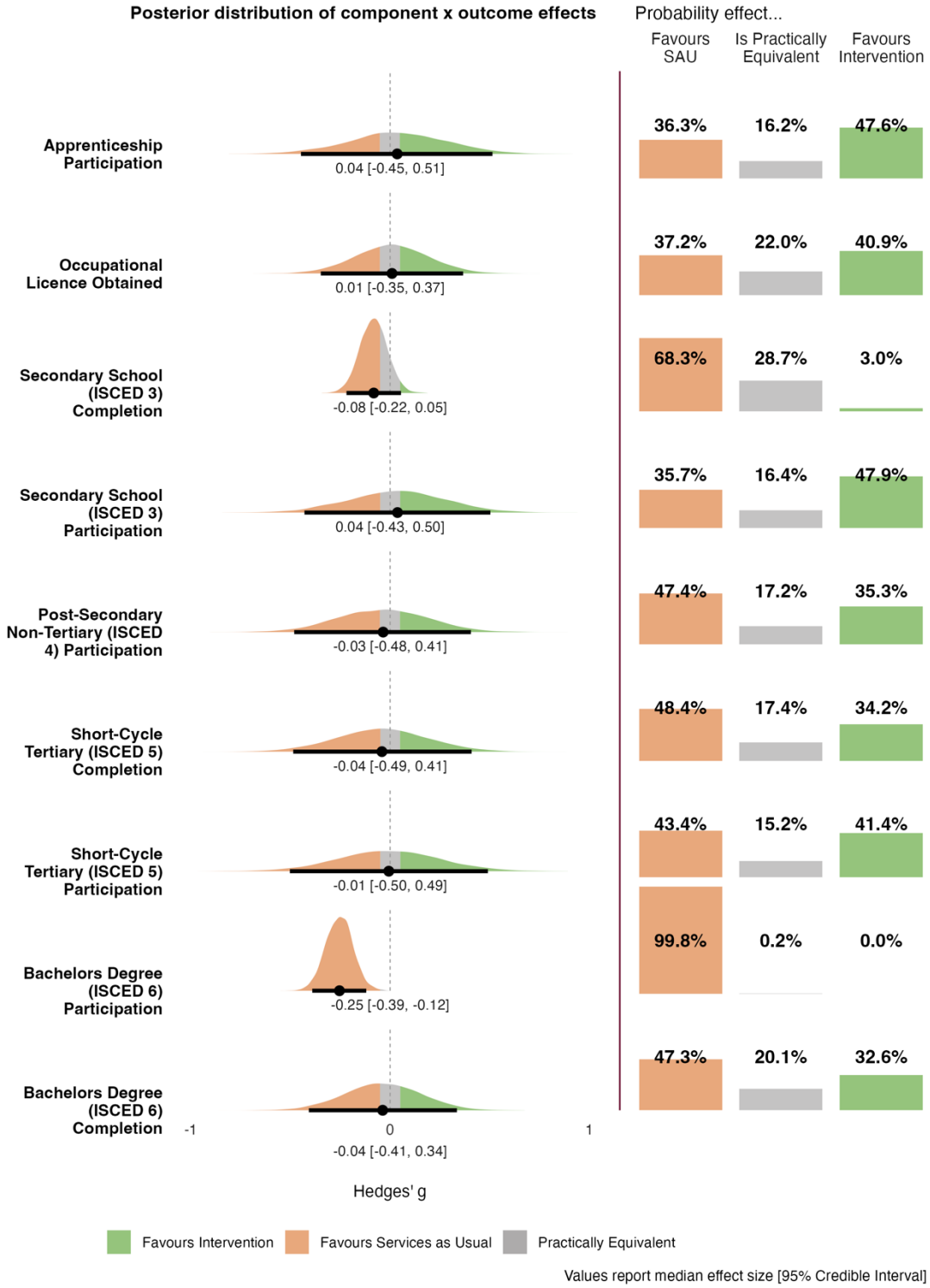
Education and Skills

The impact of Employment Coaching on education and skills outcomes is presented in Figure 68. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls in the little or no impact range (g=0.04).
- *Occupational licence attainment* — the median estimate falls in the little or no impact range (g=0.01).
- *Secondary school completion* — the median effect falls within the low impact range (*g*=-0.08) and favours SAU.
- *Bachelor's degree participation* — the median estimate falls in the high impact range (*g*=-0.25) and favours SAU.

Overall, the results suggest Employment Coaching does not have a positive effect on most employment and skills outcomes and may have a negative one.

Figure 68 Impact of Employment Coaching on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of employment coaching between females and males falls within the bounds of little or no effect: *g*=0.02, 95% CrI [-0.03, 0.063].
- **Posterior probabilities** — there is a 77% chance the impact of employment coaching is higher in all-female study populations and a 33% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=-0.01 95% CrI [-0.05, 0.02] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.09, 95% CrI [-0.36, 0.18].

- **Posterior probabilities** — there is a 25% chance the impact of Employment Coaching increases with the mean study age.

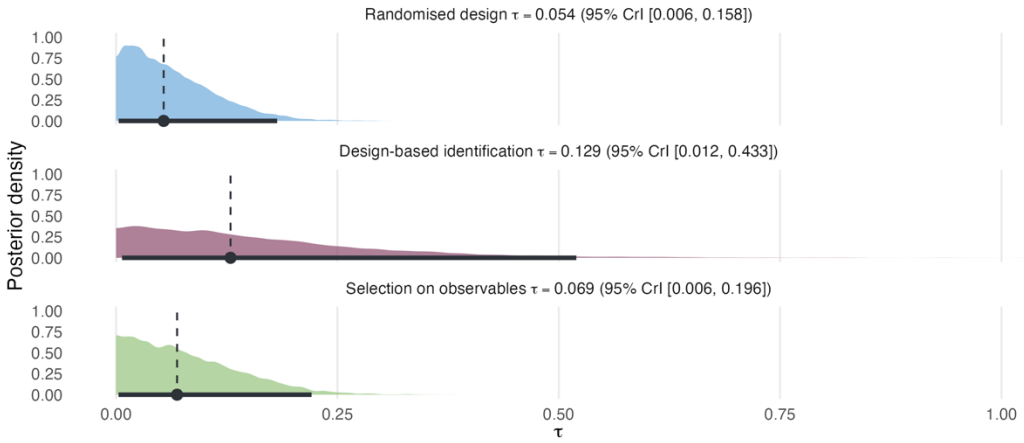
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 69 shows the component-specific heterogeneity by study design. As in the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. The median and spread for each distribution is lower the overall results, however there is no meaningful change from the conclusion that SOO and DBI studies show greater variability.

Figure 69 Posterior distribution of between study heterogeneity (τ) by for Employment Coaching by study design



Financial Assistance

Key findings

- **Financial Assistance may support the attainment of occupational licences.** Median effects for *Occupational Licence Obtainment* are high, with a substantial probability that impacts favour the intervention (Pr > 0.05 = 0.74) and a 50% chance that effects are high in magnitude.
- **For Current Unemployment, effects strongly favour services as usual.** The probability of a high-impact effect favouring SAU is effectively certain (Pr > 0.2 = 1).
- **Impacts vary by population characteristics**. Effects are likely to be larger in all-female study populations (77%), though differences fall within the range of little or no impact. Effects are also likely to increase with mean study age (81%), with a medium-sized difference between studies with mean ages of 24 versus 16.
- **How to make sense of this.** It is possible that the impact of Financial Assistance on occupational licence attainment is linked to downstream labour market outcomes. Financial assistance commonly covers job-related expenses, including the costs of industry credentials necessary to secure work. These accreditations may act as an enabler of employment and of increased hours worked.

Definition

Financial assistance services provide targeted support to help jobseekers overcome financial barriers that hinder their search for employment. These services may include grants or subsidies for transportation costs to interviews, professional attire, or other job-related expenses (e.g., attainment of driving licence or industry credential necessary to secure work) that may otherwise provide a barrier to the jobseeker.

Evidence profile

A summary of the evidence used to inform the analysis of Financial Assistance is summarised in Table 31. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 31 Evidence profile for Financial Assistance

SUMMARY	COUNT			
Number of studies	30			
Number of effect sizes	92			
Study design	RE: 16	SOO: 10	DBI: 4	
Risk of bias	Acceptable: 17		High: 13	
Study design x risk of bias	Acceptable High	RE: 11 RE: 5	SOO: 3 SOO: 7	DBI: 3 DBI: 1
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=17); Recent Employment (n=8); Currently Unemployed (n=1); Currently NEET (n=3); Currently Not in the Labour Force (n=1)			
Employment Compensation	Labour Earnings (n=11); Wages (n=2)			
Employment duration	Period Employed (n=4)			
Hours Worked	Hours Worked (n=4)			
Education & Skills	Secondary School (ISCED 3) Participation (n=1); Secondary School (ISCED 3) Completion (n=12); Bachelors Degree (ISCED 6) Participation (n=4); Bachelors Degree (ISCED 6) Completion (n=2); Short-Cycle Tertiary (ISCED 5) Participation (n=2); Short-Cycle Tertiary (ISCED 5) Completion (n=3); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=1); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=2); Apprenticeship Participation (n=1); Occupational Licence Obtained (n=3)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Financial Assistance. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

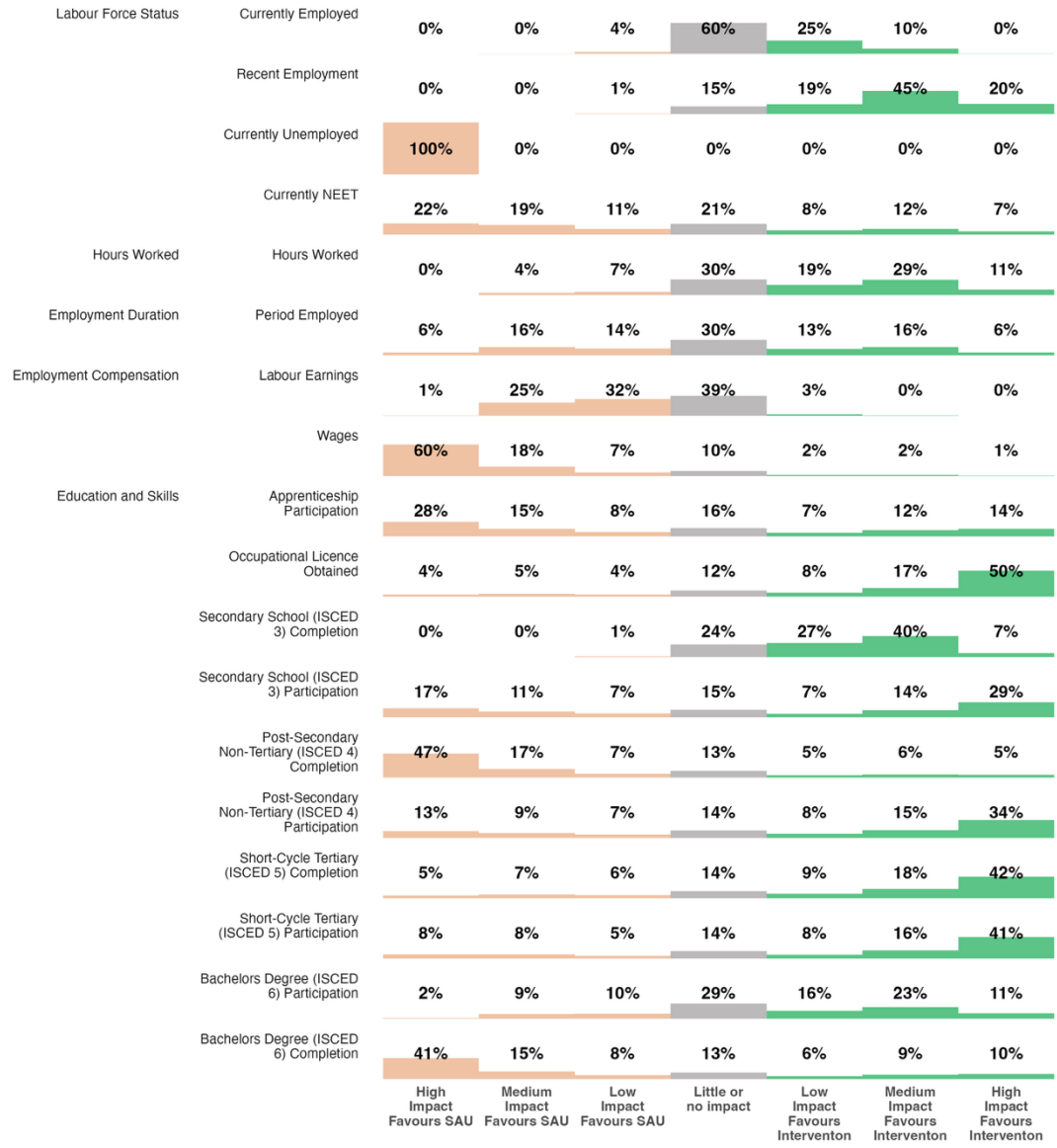
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 70 shows the posterior probability that the effect of Financial Assistance on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 70 Probability of the scale of impact of Financial Assistance



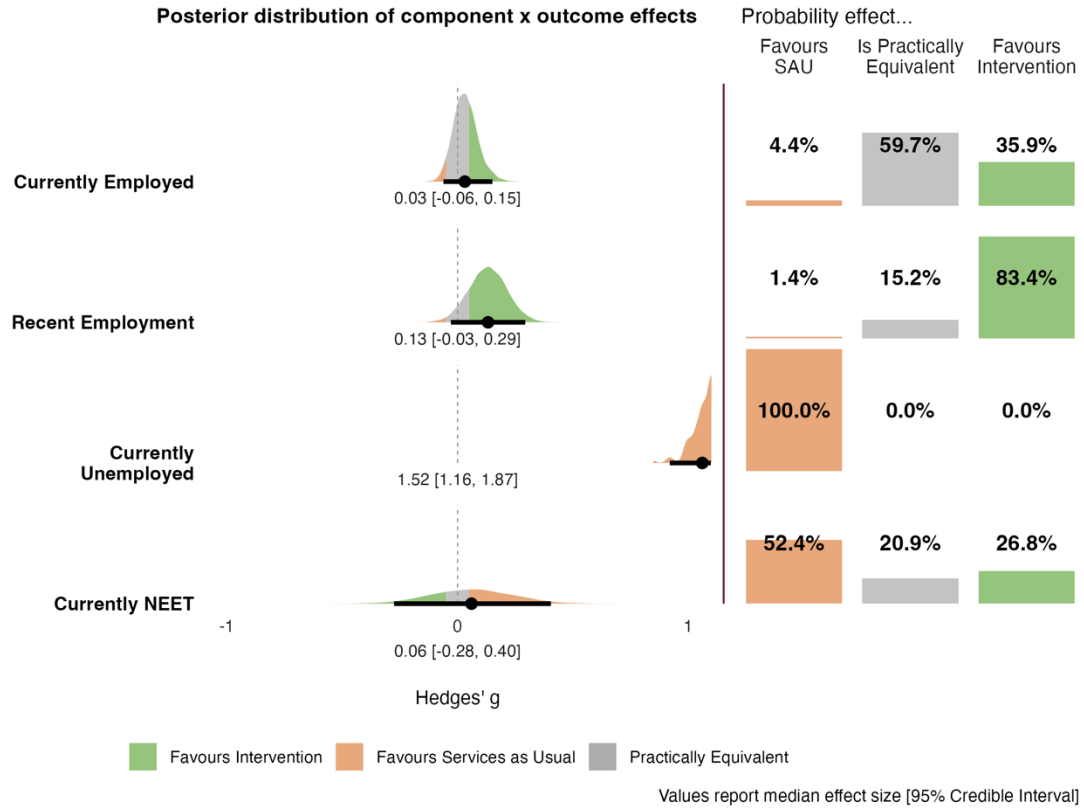
Labour Force status

The impact of Financial Assistance on labour force outcomes is presented in Figure 71.

- The median impact for Currently Unemployed is very high and favours SAU. A low median impact estimate favouring SAU is also observed for Currently NEET. A low median impact result favouring the intervention is observed for Recent Employment. There is little or no impact on Currently Employed.

- The very high negative effect for Currently Unemployed is informed by a single study and should be considered with that in mind.
- The probability of any positive impact is high for Recent Employment (83%) and low for Currently Employed (36%).
- The probability of a medium (45%) or high (20%) impact for Recent Employment is moderate (65%).
- Overall, these findings suggest that Financial Assistance may have a positive impact on Recent Employment.

Figure 71 Impact of Financial Assistance on Labour Force status

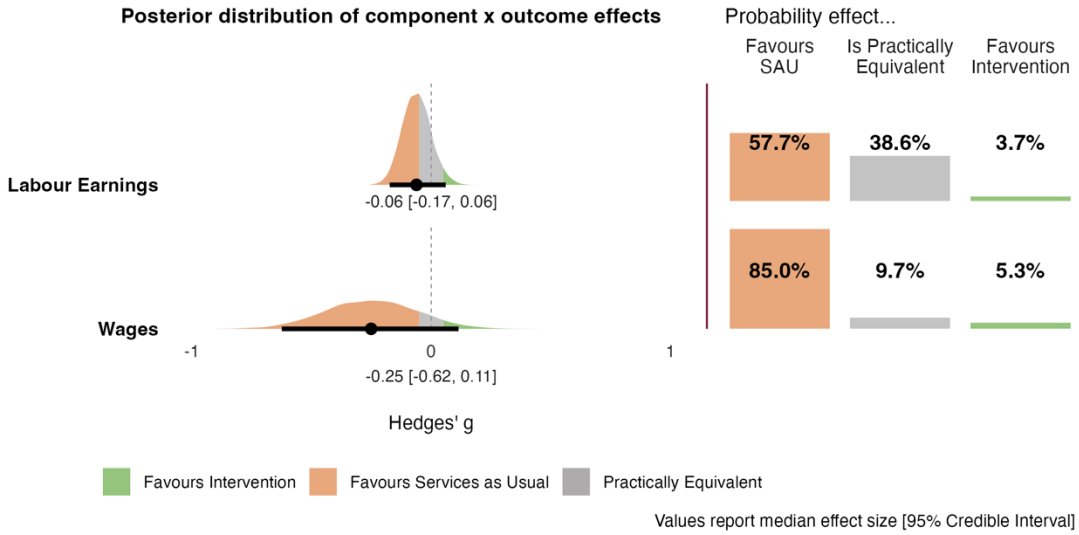


Employment compensation

The impact of Financial Assistance on employment compensation outcomes is presented in Figure 72.

- Median estimates for both Labour Earnings and Wages are negative and favour SAU.
- Overall, these results suggest little evidence that Financial Assistance improves employment compensation.

Figure 72 Impact of Financial Assistance on Employment compensation

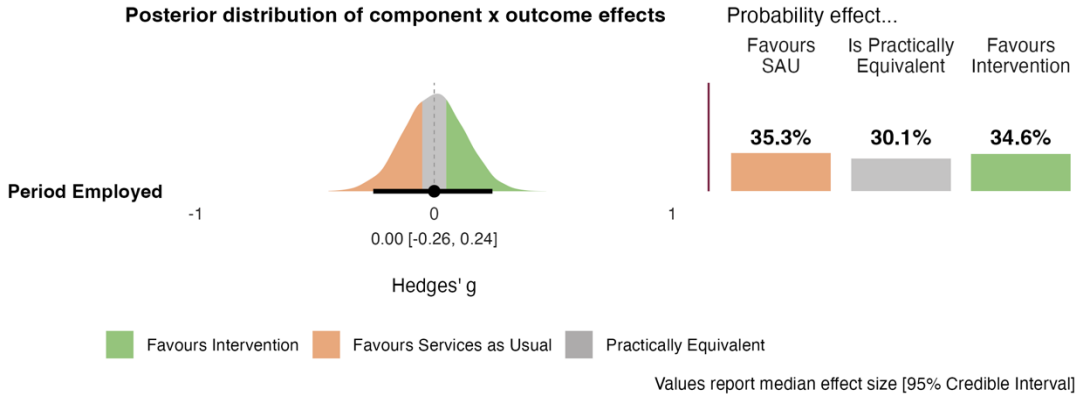


Employment duration

The impact of Financial Assistance on employment duration outcomes is presented in Figure 73.

- The median estimate falls within the range of little or no impact.
- The probability of any effect favouring the intervention is 35%.
- Overall, Financial Assistance is unlikely to increase time spent in employment.

Figure 73 Impact of Financial Assistance on Employment duration

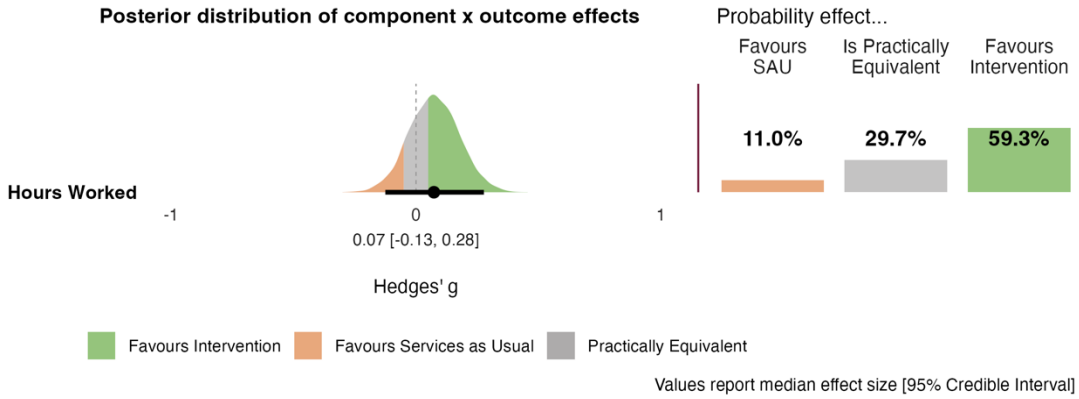


Hours worked

The impact of Financial Assistance on Hours Worked is presented in Figure 74.

- The median estimate favours the intervention and falls within the low impact range.
- The probability of any effect favouring the intervention is 59%.
- There is a probability of a medium (29%) or high (11%) impact is around 40%.
- Overall, Financial Assistance may increase Hours Worked.

Figure 74 Impact of Financial Assistance on Hours worked



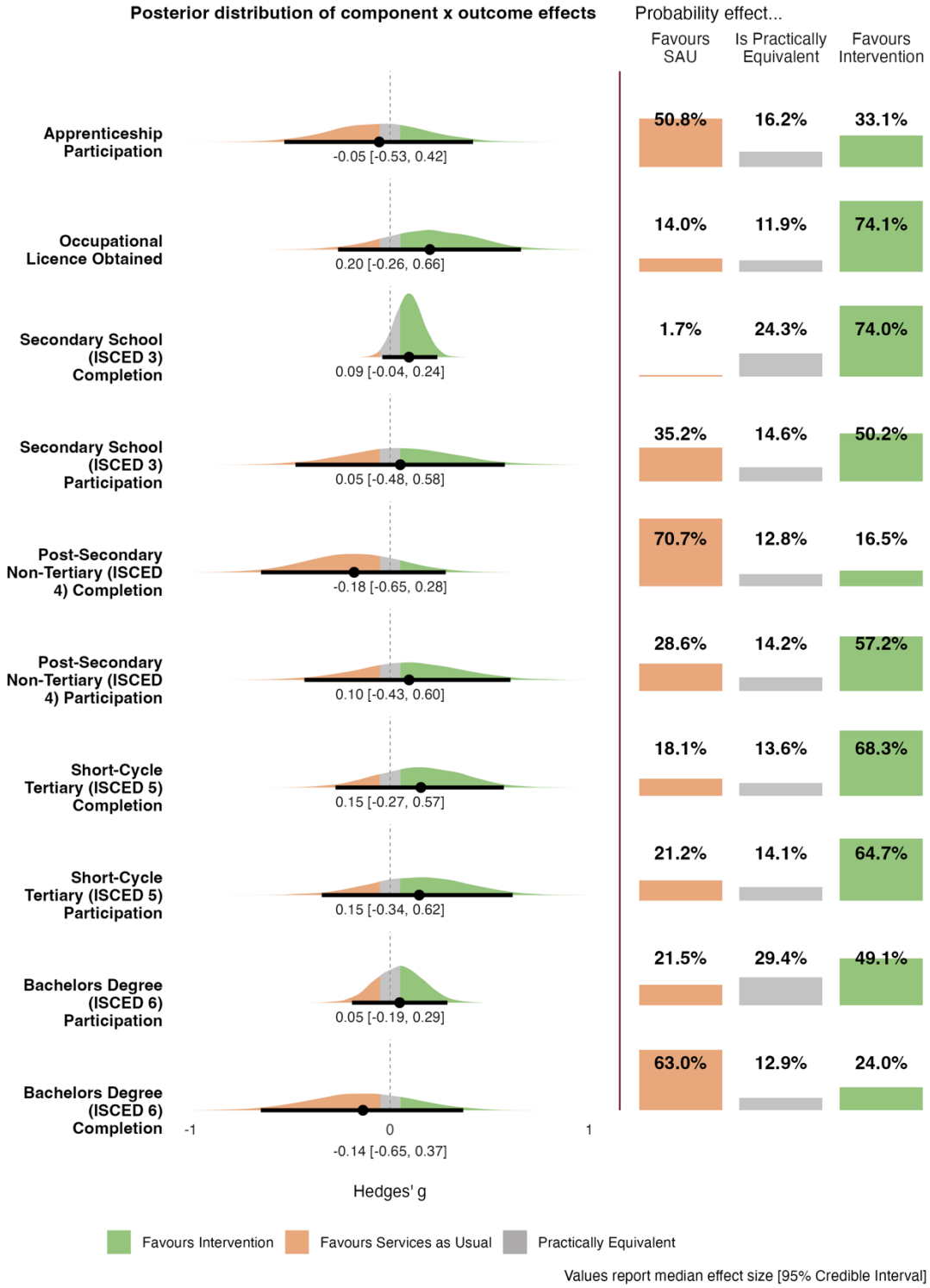
Education and Skills

The impact of Financial Assistance on education and skills outcomes is presented in Figure 75. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls in the low impact range (*g*=-0.05) and favours SAU.
- *Occupational licence attainment* — the median estimate falls on the threshold of the high-impact range (*g*=0.2), with a 74% probability of any positive effect. The probability of a medium or high impact is around two in three (67%) overall.
- *Secondary school completion* — the median effect is low (*g*=0.05), with a 50% probability of a positive impact.
- *Bachelor's degree participation* — the median effect is low (*g*=0.05), with a 49% probability of a positive impact.

The results suggest Financial Assistance may improve some skills outcomes, particularly occupational licence attainment.

Figure 75 Impact of Financial Assistance on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of financial assistance between females and males falls within the range of little or no effect: *g*=0.04, 95% CrI [-0.06, 0.13].
- **Posterior probabilities** — there is a 77.8% chance the impact of financial assistance is higher in all-female study populations and a 22.2% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g* =-0.02 95% CrI [-0.03, 0.08] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.18, 95% CrI [−0.22, 0.67].

- **Posterior probabilities** — there is an 81.3% chance the impact of Financial Assistance increases with the mean study age.

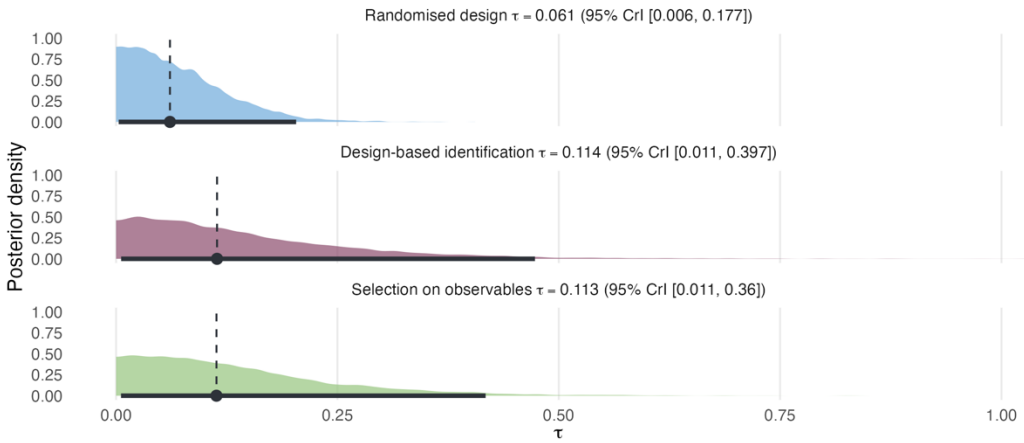
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 76 shows the component-specific heterogeneity by study design. As in the global patterns (Figure 7), τ is lowest in REs and higher in DBI and SOO, with very similar medians and spreads. This indicates that evidence from RE's is more consistent across studies, whereas greater variability is observed in SOO and DBI studies.

Figure 76 Posterior distribution of between study heterogeneity (τ) by for Financial Assistance by study design



Job Specific Technical Skills (On-the-Job Training)

Key findings

- **Job-specific technical skills delivered through on-the-job training may have small positive effects on current employment and NEET outcomes.** Median effects are low but favour the intervention for Currently Employed (Pr > 0.05 = 0.63; Pr > 0.10 = 0.22) and Currently NEET (Pr > 0.05 = 0.51; Pr > 0.10 = 0.42), indicating a moderate likelihood that impacts favour the intervention but are more likely to be low in magnitude.
- **On-the-job technical training is also associated with positive effects on employment compensation.** There is a high probability (78%) that impacts favour the intervention for both Labour Earnings and Wages, with effects most likely to be medium in magnitude.
- **Impacts do not appear to vary by population characteristics.** Effects are similar between all-male and all-female study populations and do not show systematic variation with mean study age.
- **How to make sense of this.** On-the-job technical training builds occupation-specific skills that are directly applicable in the workplace. While short-term effects on employment status are modest, improvements in earnings and wages suggest productivity gains, and links to apprenticeship participation indicate potential for longer-term labour market benefits.

Definition

These programmes often have an occupational focus and have relatively long durations, up to six months and sometimes more. The roles are temporary and may not be paid, if the young person is receiving social welfare benefits or other government funding. Young people are placed with employers to undertake tasks associated with a competitive job in those employers. The purpose is to provide training in the specific technical and soft skills associated with the occupation. These type employment placements may be complemented by short spells of off- the-job learning but the young person will spend the large majority of their time with the employer.

Evidence profile

A summary of the evidence used to inform the analysis of Job Specific Technical Skills (On-the-Job Training) is summarised in Table 32. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 32 Evidence profile for Job Specific Technical Skills (On-the-Job Training)

SUMMARY	COUNT			
Number of studies	43			
Number of effect sizes	114			
Study design	RE: 19	SOO: 21	DBI: 3	
Risk of bias	Acceptable: 27		High: 16	
Study design x risk of bias	Acceptable High	RE: 11 RE: 8	SOO: 14 SOO: 7	DBI: 2 DBI: 1
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=23); Recent Employment (n=8); Currently Unemployed (n=5); Currently NEET (n=1)			
Employment Compensation	Labour Earnings (n=11); Wages (n=9)			
Employment duration	Period Employed (n=3)			
Hours Worked	Hours Worked (n=8)			
Education & Skills	Secondary School (ISCED 3) Participation (n=1); Secondary School (ISCED 3) Completion (n=7); Bachelors Degree (ISCED 6) Participation (n=8); Bachelors Degree (ISCED 6) Completion (n=3); Short-Cycle Tertiary (ISCED 5) Participation (n=1); Short-Cycle Tertiary (ISCED 5) Completion (n=2); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=2); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=1); Apprenticeship Participation (n=2); Occupational Licence Obtained (n=2)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Job Specific Technical Skills (On-the-Job Training). For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 77 shows the posterior probability that the effect of Job Specific Technical Skills (On-the-Job Training) on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 77 Probability of the scale of impact of Job Specific Technical Skills (On-the-Job Training)



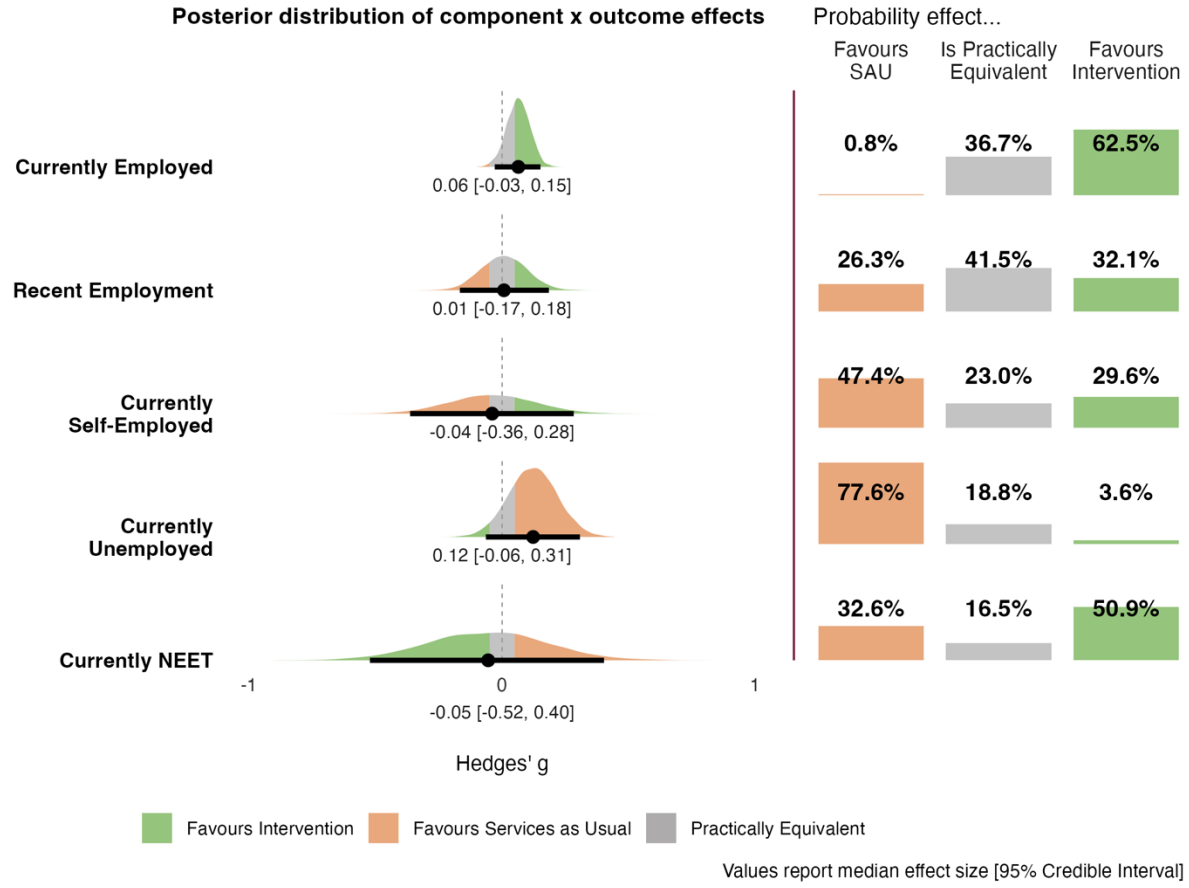
Labour Force status

The impact of Job Specific Technical Skills (On-Job Training) on labour force outcomes is presented in Figure 78.

- Median estimates across outcomes are inconsistent. Results for both Currently Employed and Currently NEET favour the intervention, but are low in magnitude. Estimates for Currently Self-Employed and Recent Employment fall in the range of little or no effect. While the median estimate for Currently Unemployed is a medium sized effect favouring SAU.
- The probability of an effect favouring the intervention is more than one-in-two for Currently Employed (Pr > 0.05 = 0.63) and Currently NEET (Pr > 0.05 = 0.51).
- The probability of a high or medium impact for both Recent Employment and Currently NEET is low, suggesting that any positive impact is most likely to be low in magnitude.

Overall, these findings suggest that Job Specific Technical Skills (On-the-Job Training) has a moderate probability of having a positive effect on current employment.

Figure 78 Impact of Job Specific Technical Skills (On-the-Job Training) on Labour Force status



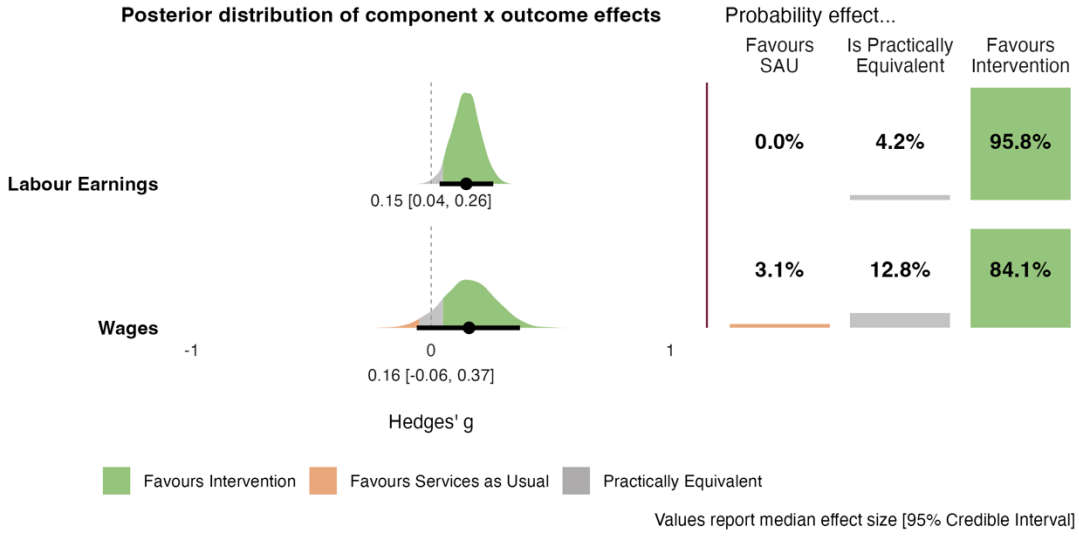
Employment compensation

The impact of Job Specific Technical Skills (On-the-Job Training) on employment compensation outcomes is presented in Figure 79.

- Median estimates for both Labour Earnings and Wages favour the intervention and fall within the medium impact range.
- The probability of any positive impact for both outcomes is high: 96% for Labour Earnings and 92% for Wages.
- For both outcomes, a medium magnitude impact is most likely.

Overall, these results suggest that there is a very high probability that Job Specific Technical Skills (On-the-Job Training) has a positive impact on employment compensation.

Figure 79 Impact of Job Specific Technical Skills (On-the-Job Training) on Employment compensation



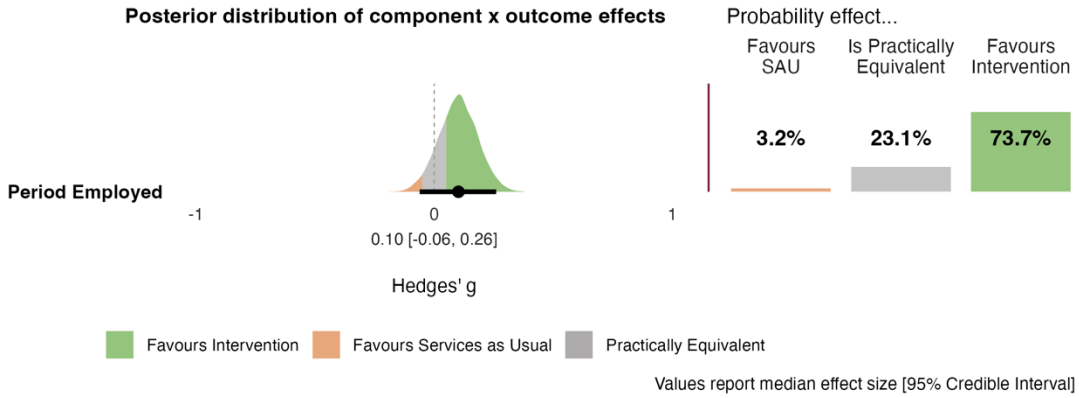
Employment duration

The impact of Job Specific Technical Skills (On-the-Job Training) on employment duration outcomes is presented in Figure 80.

- The median estimate favours the intervention and falls on the threshold of the medium impact range.
- The probability of any positive impact favouring the intervention is 74%.
- A medium impact magnitude is most likely (40%).

Overall, there is a high probability that Job Specific Technical Skills (On-the-Job Training) increases employment duration, however the effect is more likely to be low or medium.

Figure 80 Impact of Job Specific Technical Skills (On-the-Job Training) on Employment duration

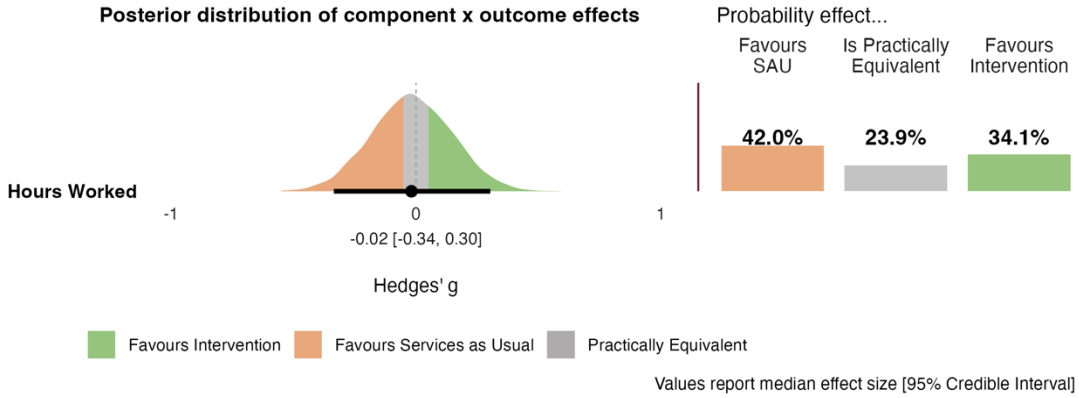


Hours worked

The impact of Job Specific Technical Skills (On-the-Job Training) on hours worked is presented in Figure 81.

- The median estimate falls within the no or little impact range.
- The probability of any positive impact favouring the intervention is low (Pr > 0.05 = 0.34), and the probability that the positive impact is medium or high is around one in four (Pr > 0.1 = 0.24).
- Overall, Job Specific Technical Skills (On-Job Training) does not appear to increase hours worked.

Figure 81 Impact of Job Specific Technical Skills (On-the-Job Training) on Hours worked



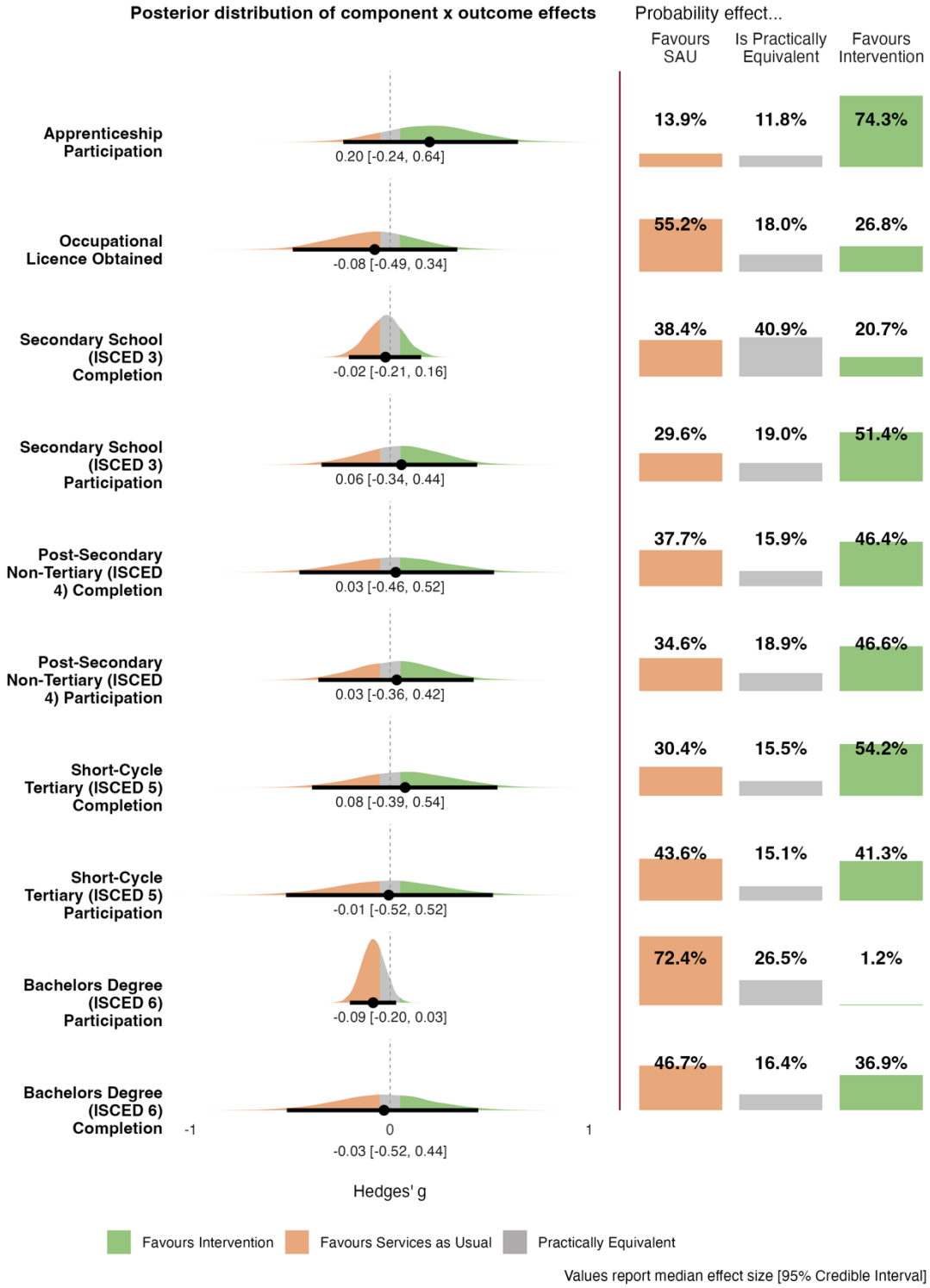
Education and Skills

The impact of Job Specific Technical Skills (On-the-Job Training) on education and skills outcomes is presented in Figure 82. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls on the threshold of the high-impact range (*g*=0.20), with an 74% probability that the impact favours the intervention. There is a 50% probability of a high impact.
- *Occupational licence attainment* — the median estimate falls in the low impact range (*g*=-0.08) and favours SAU.
- *Secondary school completion* — the median effect falls within the range of little or no effect (*g*=–0.02).
- *Bachelor's degree participation* — the median estimate falls within the low impact range and favours SAU.

Overall, Job Specific Technical Skills (On-the-Job Training) has little or no effect of the majority of education and skills outcomes, the results suggest may increase apprenticeship participation.

Figure 82 Impact of Job Specific Technical Skills (On-Job Training) on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of Job Specific Technical Skills (On-the-Job Training) between females and males falls within the bounds of little or no effect: *g*=0.01, 95% CrI [-0.06, 0.08].
- **Posterior probabilities** — there is a 60.8% chance the impact of Job Specific Technical Skills (On-the-Job Training) is higher in all-female study populations and a 39.2% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=-0.01 95% CrI [-0.03, 0.02] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.04, 95% CrI [-0.26, 0.16].

- **Posterior probabilities** — there is a 33.5% chance the impact of Job Specific Technical Skills (On-Job Training) increases with the mean study age.

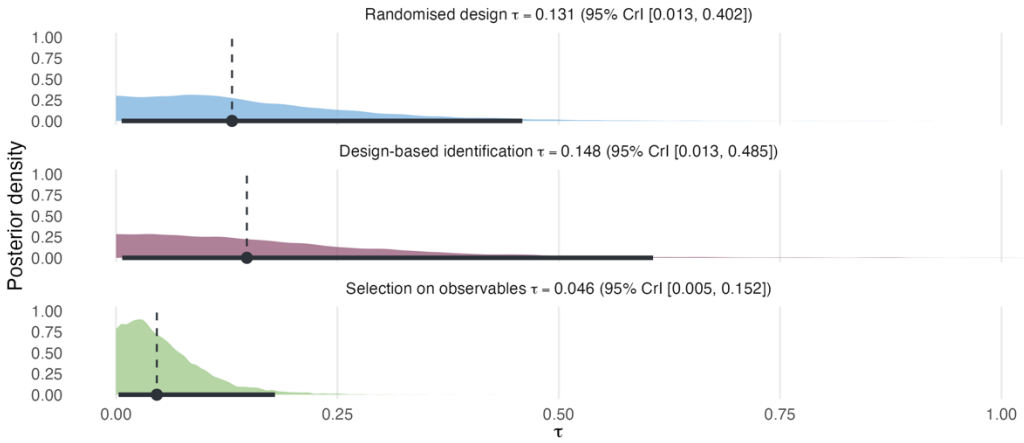
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 83 shows the component-specific heterogeneity by study design. Relative to the global patterns (Figure 7), heterogeneity is higher for REs and slightly higher for DBI, indicating greater between-study variability in the more strongly identified studies. By contrast, SOO studies show a smaller and tighter distribution than in the overall results, suggesting comparatively consistent findings among these studies.

Figure 83 Posterior distribution of between study heterogeneity (τ) by for Job Specific Technical Skills (On-the-Job Training) by study design



Paid Temporary Work Experience

Key findings

- **Paid Temporary Work Experience may reduce current unemployment.** The median effect on Current Unemployment is high, with a very high probability that impacts favour the intervention (Pr > 0.05 = 0.96) and a greater than even chance that the effect is high in magnitude (Pr > 0.2 = 0.55).
- **Paid Temporary Work Experience is also associated with increased participation in bachelor's degrees.** There is a high probability of a positive effect (87%), though impacts are most likely to be medium rather than high in magnitude.
- **Impacts do not appear to vary by population characteristics.** Effects are similar between all-male and all-female study populations and do not show systematic variation with mean study age.
- **How to make sense of this.** The labour market impacts of paid work experience are high, but the impact varies from unpaid work experience (see below), which also impacts on current NEET status, and wages, but not on bachelor's degree participation. Work experience delivers workplace exposure, skill development, and opportunities to build social capital. Payment may further engagement and persistence, by breaking down resource barriers to ongoing engagement, which may be particularly important for marginalised young people. Full engagement in work experience may help participants to translate work experience into improved market attachment and onward educational participation.

Definition

These programmes offer paid temporary positions to young people. The duration tends to be much shorter and the purpose is to build insights into the world of work and to 'practise' the behavioural skills needed to sustain work. This could include internships. Some paid work experience programmes may be for employers advertising vacancies. In this case, the employer may guarantee an interview at the end, which may mean the young person can move into permanent employment.

Evidence profile

A summary of the evidence used to inform the analysis of Paid Temporary Work Experience is summarised in Table 33. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 33 Evidence profile for Paid Temporary Work Experience

SUMMARY	COUNT			
Number of studies	53			
Number of effect sizes	165			
Study design	RE: 26	SOO: 20	DBI: 7	
Risk of bias	Acceptable: 31		High: 22	
Study design x risk of bias	Acceptable High	RE: 26 RE: 3	SOO: 9 SOO: 11	DBI: 4 DBI: 3
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=26); Recent Employment (n=7); Currently Unemployed (n=6); Currently NEET (n=3); Currently Not in the Labour Force (n=2)			
Employment Compensation	Labour Earnings (n=22); Wages (n=6)			
Employment duration	Period Employed (n=6)			
Hours Worked	Hours Worked (n=11)			
Education & Skills	Secondary School (ISCED 3) Participation (n=3); Secondary School (ISCED 3) Completion (n=15); Bachelors Degree (ISCED 6) Participation (n=6); Bachelors Degree (ISCED 6) Completion (n=4); Short-Cycle Tertiary (ISCED 5) Participation (n=3); Short-Cycle Tertiary (ISCED 5) Completion (n=2); Post-Secondary Non-Tertiary (ISCED 4) Participation (n=3); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=2); Apprenticeship Participation (n=1); Occupational Licence Obtained (n=4)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Paid Temporary Work Experience. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 84 shows the posterior probability that the effect of Paid Temporary Work Experience on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 84 Probability of the scale of impact of Paid Temporary Work Experience



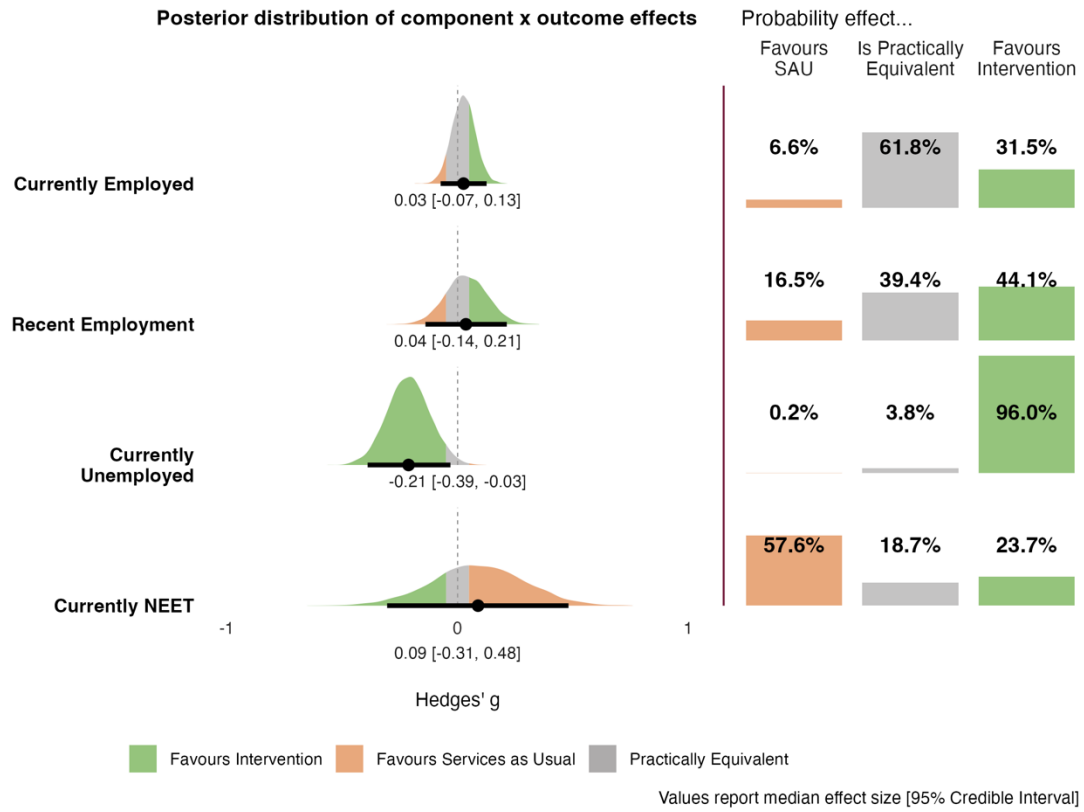
Labour Force status

The impact of Paid Temporary Work Experience on labour force outcomes is presented in Figure 85.

- Median estimates vary between outcomes. The median estimate for Currently Unemployed is a large effect favouring the intervention. The result for Currently NEET is low effect favouring SAU. The intervention had little or no effect on the remaining two outcomes.

- The probability the effect favours the intervention is very high for Currently Unemployed (Pr > 0.05 = 0.96).
- The probability of a medium (33%) or high (55%) impact is very high for Currently Employed (88%).
- Overall, these findings suggest that Paid Temporary Work Experience can have a positive impact on reducing Currently Unemployment.

Figure 85 Impact of Paid Temporary Work Experience on Labour Force status

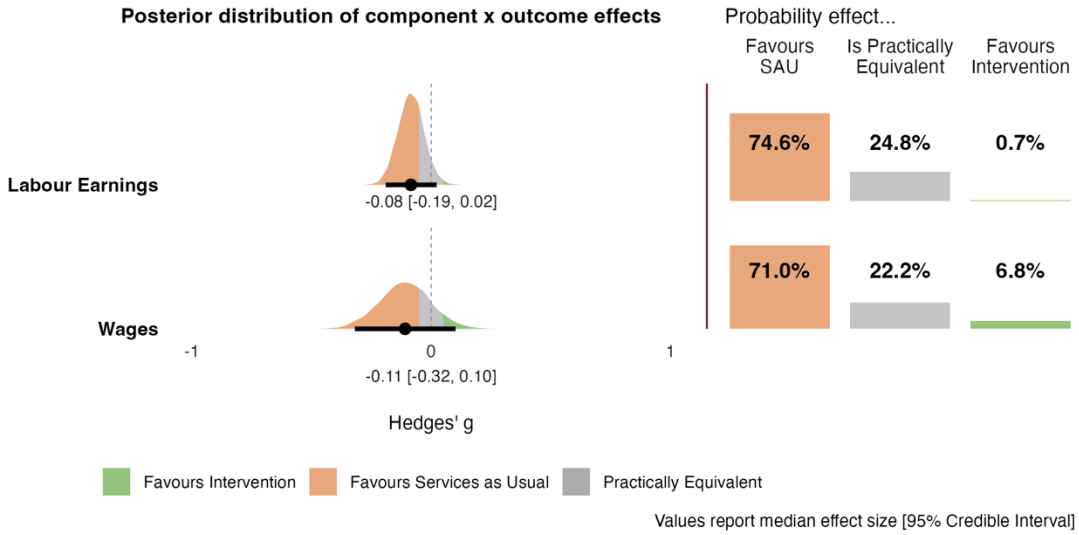


Employment compensation

The impact of Paid Temporary Work Experience on employment compensation outcomes is presented in Figure 86.

- Median estimates for both Labour Earnings and Wages are negative and favour SAU.
- The probability that the effect favours SAU is high: 71% for Wages and 75% for Labour Earnings.
- Overall, these results suggest that Paid Temporary Work Experience does not improve employment compensation outcomes.

Figure 86 Impact of Paid Temporary Work Experience on Employment compensation

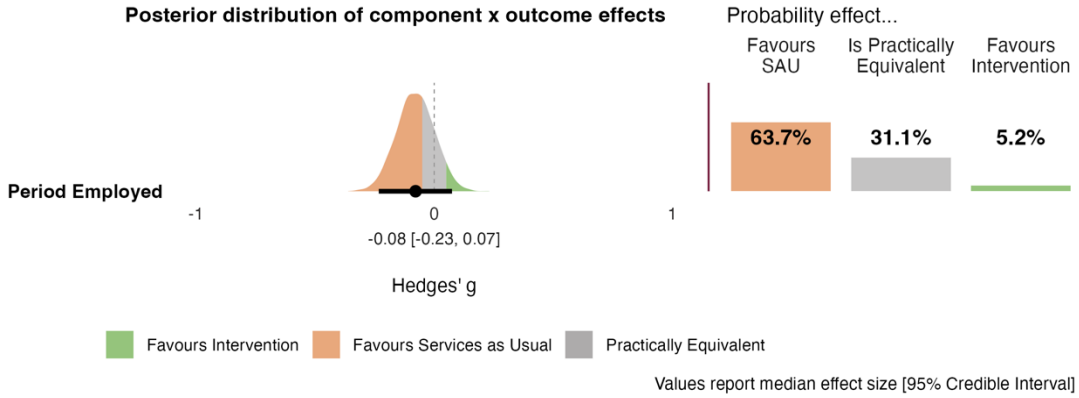


Employment duration

The impact of Paid Temporary Work Experience on employment duration outcomes is presented in Figure 87.

- The median estimate for Period Employed falls within the low impact range and favours SAU.
- The probability the effect favours SAU is nearly two-in-three (Pr < 0.05 = 0.64).
- Overall, Paid Temporary Work Experience does not appear to increase time spent in employment.

Figure 87 Impact of Paid Temporary Work Experience on Employment Duration

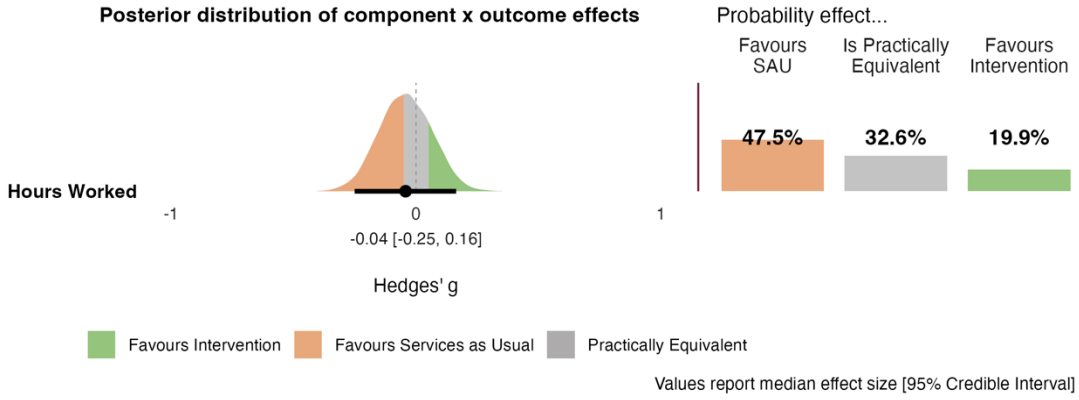


Hours worked

The impact of Paid Temporary Work Experience on hours worked is presented in Figure 88.

- The median estimate falls within the range or little or no effect.
- Overall, Paid Temporary Work Experience does not appear to increase Hours Worked.

Figure 88 Impact of Paid Temporary Work Experience on Hours worked



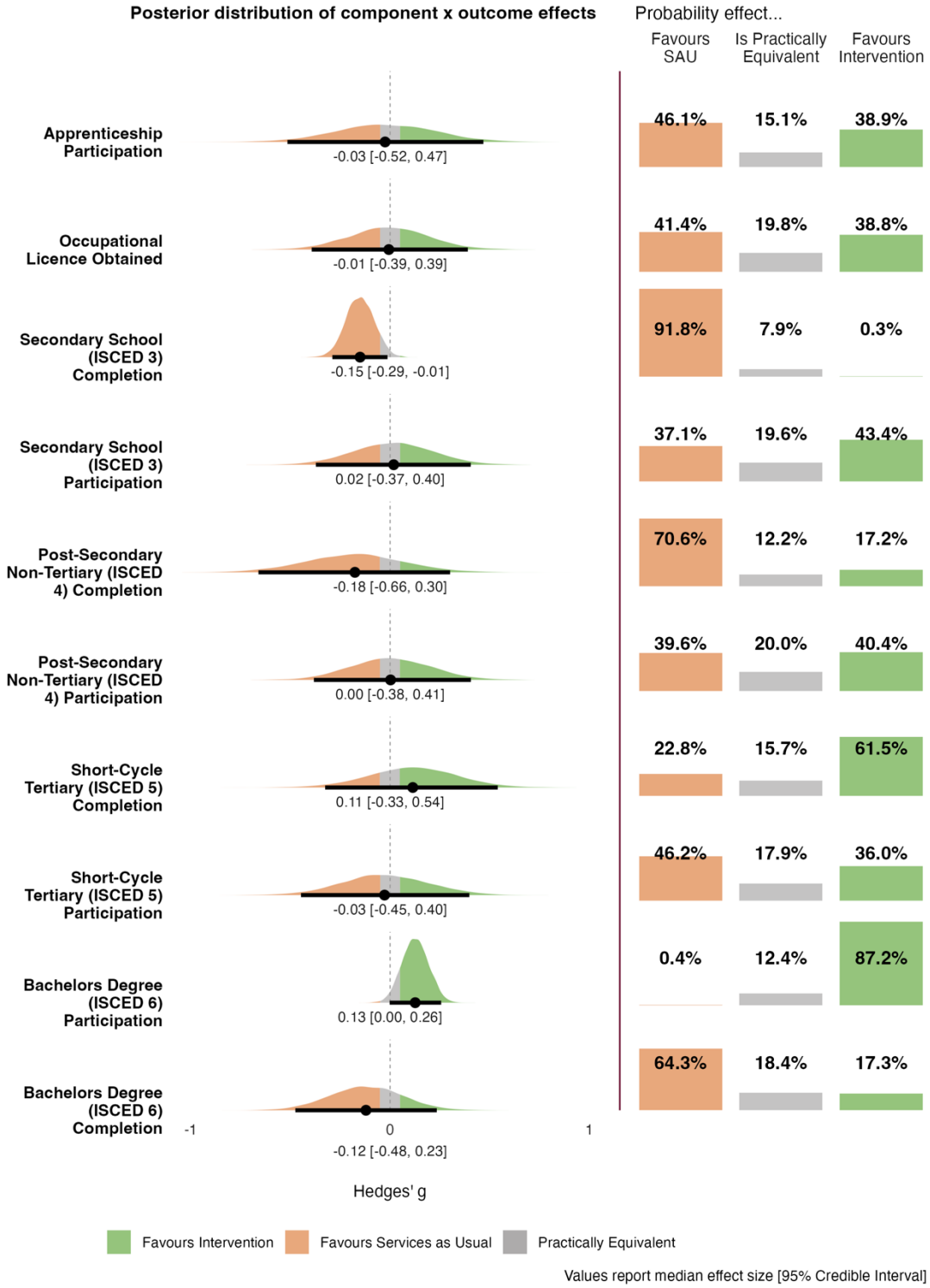
Education and Skills

The impact of Paid Temporary Work Experience on education and skills outcomes is presented in Figure 89. Because there is a wide range of outcomes, we focus here on four that are most salient for policymakers:

- *Apprenticeship participation* — the median estimate falls within the range of little or no effect.
- *Occupational licence attainment* — the median estimate falls within the range of little or no effect.
- *Secondary school completion* — the median effect falls within the medium impact range (*g*=-0.15) and favours SAU.
- *Bachelor's degree participation* — the median estimate falls in the median impact range (*g*=0.13). The probability of a positive impact favouring the intervention is high (87%); however it is most likely to be medium (52%).

Overall, while most education outcomes are likely to be low or uncertain, the results suggest Job Specific Technical Skills (Off-the-Job Training) may meaningfully increase participation in a bachelor's degree.

Figure 89 Impact of Paid Temporary Work Experience on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of Paid Temporary Work Experience between females and males is within the low impact range: *g*=0.05, 95% CrI [-0.01, 0.12].
- **Posterior probabilities** — there is a 95.4% chance the impact of Paid Temporary Work Experience is higher in all-female study populations and a 4.6% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=-0.02, 95% CrI [-0.03, 0.28] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=-0.02, 95% CrI [-0.26, 0.23].

- **Posterior probabilities** — there is a 44.9% chance the impact of Paid Temporary Work Experience increases with the mean study age.

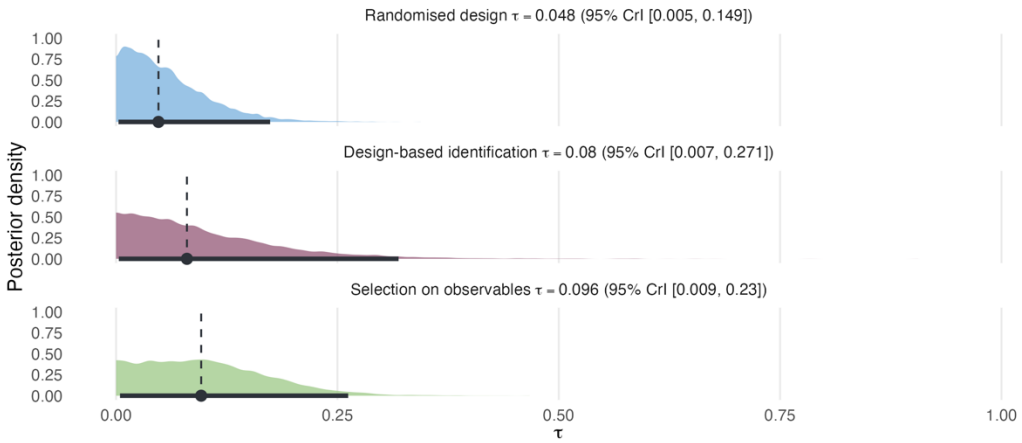
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 90 shows the component-specific heterogeneity by study design. As in the global patterns (Figure 7), heterogeneity is lowest in RE's and higher in DBI and SOO studies. However, relative to the global distributions, τ is smaller across all three study designs indicating relatively low between-study variability for paid temporary work experience.

Figure 90 Posterior distribution of between study heterogeneity (τ) by for Paid Temporary Work Experience by study design



Unpaid Temporary Work Experience

Key findings

- **Unpaid Temporary Work Experience shows positive effects on some labour market outcomes.** Median effects are high for Currently NEET (Pr > 0.05 = 0.96; Pr > 0.2 = 0.86) and Currently Employed (Pr > 0.05 ~ 1; Pr > 0.2 = 0.89), indicating a high likelihood that impacts favour the intervention and are high in magnitude.
- **Unpaid Temporary Work Experience likely increases wages.** There is a reasonable probability of a positive effect on Wages (68%) and a greater than even chance that the impact is at least medium in magnitude.
- **Impacts do not meaningfully vary by population characteristics.** Effects are very likely to be larger in all-male study populations (98%), though differences are small in magnitude. Effects are also more likely to increase with mean study age, with a medium-sized difference between studies with mean ages of 24 versus 16.
- **How to make sense of this.** Aside from the absence of payment, unpaid and paid work experience are likely to share many features. Differences in observed impacts between these two components, which centre on unpaid work experience having high impact on current employment as well as current NEET status, and on wages but no effect on participation in bachelor's degrees, may therefore reflect the populations served, delivery contexts, or the combination of components provided alongside work experience. This pattern warrants closer examination of programme design and targeting to better understand the mechanisms at play.

Definition

These programmes offer unpaid temporary positions to young people. The duration tends to be much shorter and the purpose is to build insights into the world of work and to 'practise' the behavioural skills needed to sustain work. This could include internships. Some unpaid work experience programmes may be for employers advertising vacancies. In this case, the employer may guarantee an interview at the end, which may mean the young person can move into permanent employment.

Evidence profile

A summary of the evidence used to inform the analysis of Unpaid Temporary Work Experience is summarised in Table 34. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 34 Evidence profile for Unpaid Temporary Work Experience

SUMMARY	COUNT			
Number of studies	18			
Number of effect sizes	56			
Study design	RE: 12	SOO: 5	DBI: 1	
Risk of bias	Acceptable: 8		High: 10	
Study design x risk of bias	Acceptable High	RE: 6 RE: 6	SOO: 1 SOO: 4	DBI: 1 DBI: 0
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=10); Recent Employment (n=3); Currently Unemployed (n=2); Currently NEET (n=1); Currently Not in the Labour Force (n=1)			
Employment Compensation	Labour Earnings (n=8); Wages (n=4)			
Employment duration	Period Employed (n=2)			
Hours Worked	Hours Worked (n=4)			
Education & Skills	Secondary School (ISCED 3) Completion (n=5); Bachelors Degree (ISCED 6) Participation (n=2); Bachelors Degree (ISCED 6) Completion (n=1); Post-Secondary Non-Tertiary (ISCED 4) Completion (n=1); Occupational Licence Obtained (n=1)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Unpaid Temporary Work Experience. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

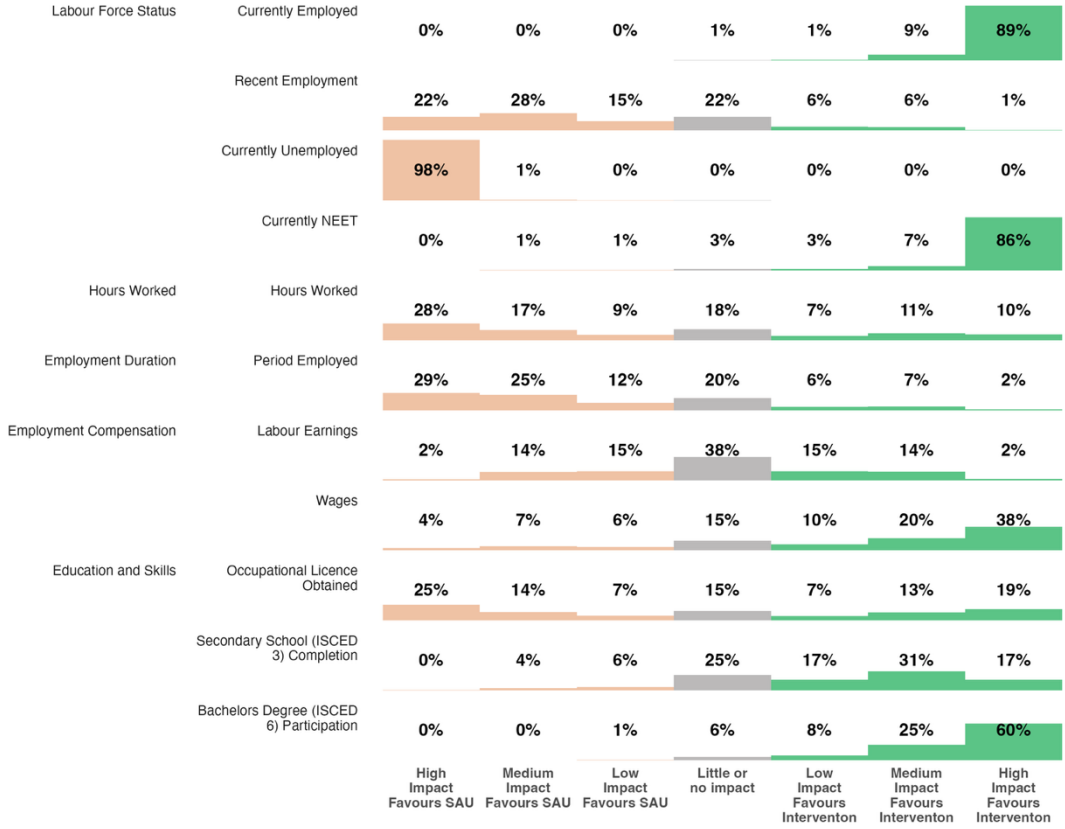
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 91 shows the posterior probability that the effect of Unpaid Temporary Work Experience on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 91 Probability of the scale of impact of Unpaid Temporary Work Experience



Labour Force status

The impact of Unpaid Temporary Work Experience on labour force outcomes is presented in Figure 92.

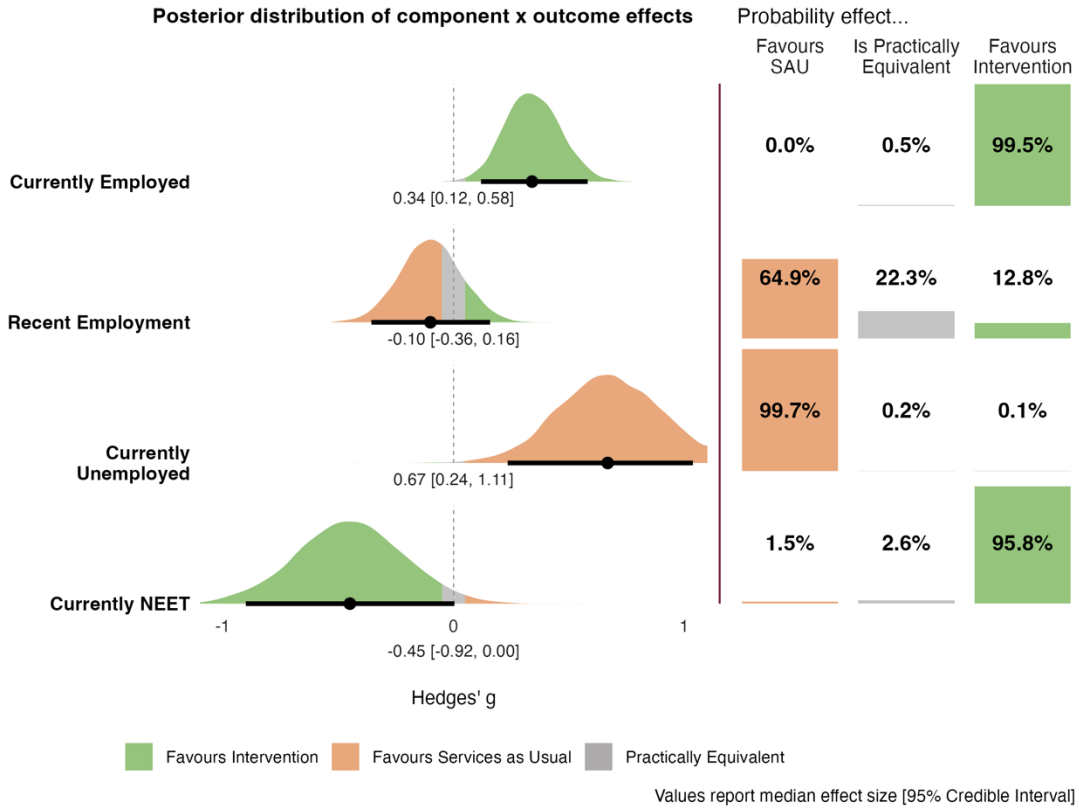
- Median estimates are inconsistent across labour market outcomes. Very high impacts favouring the intervention are observed for Currently Employed (g=0.34) and Currently NEET (g=-0.45). Very high impacts favouring SAU are also observed for Currently Unemployed (g=0.67), while a medium impact favouring SAU is observed for Recent Employment.

- It is almost certain (Pr > 0.05 ~ 100%) that the impact on Currently Employed is positive, and a high chance that the impact is high (Pr > 0.2 = 0.89).

- There is a very high probability (Pr > 0 = 0.96) that the impact on Currently NEET would favour the intervention, and a high chance that the impact is high (Pr > 0.2 = 0.86).

- Overall, these findings suggest that there is a high probability that Unpaid Temporary Work Experience can have a positive impact on two important labour market outcomes. However, a closer look at this effect is warranted, to examine why these results are inconsistent.

Figure 92 Impact of Unpaid Temporary Work Experience on Labour Force status



Employment compensation

The impact of Unpaid Temporary Work Experience on employment compensation outcomes is presented in Figure 93.

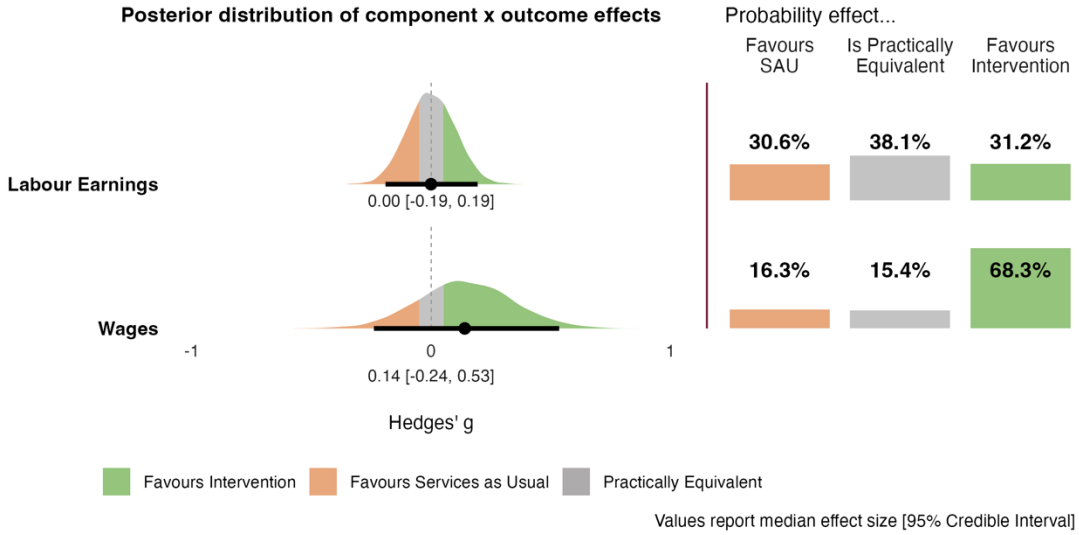
- The median estimate for Wages is medium-sized (*g*=0.14) and favours the intervention. The median estimate for Labour Earnings is in the range of little or no effect.

- The probability of any positive impact favouring the intervention is greater than two-in-three (Pr > 0.05 = 0.68) for Wages.

- The probability of a medium or high impact is greater than even for wages (Pr > 0.1 = 0.58).

- Overall, these results suggest that there is a reasonable probability that Unpaid Temporary Work Experience could have a positive impact on Wages.

Figure 93 Impact of Unpaid Temporary Work Experience on Employment compensation

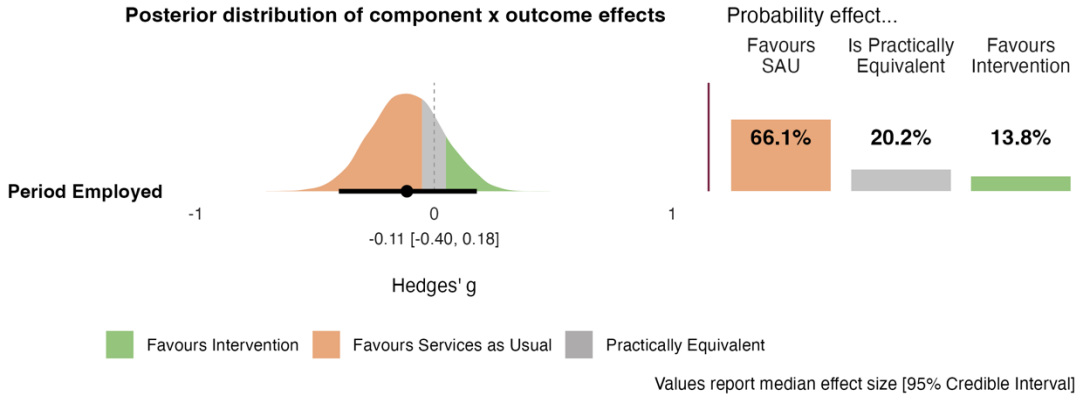


Employment duration

The impact of Unpaid Temporary Work Experience on employment duration outcomes is presented in Figure 94.

- The median estimate for Period Employed falls within the medium impact range and favours SAU.
- Overall, there is a very low probability that Unpaid Temporary Work Experience increases time spent in employment.

Figure 94 Impact of Unpaid Temporary Work Experience on Employment duration

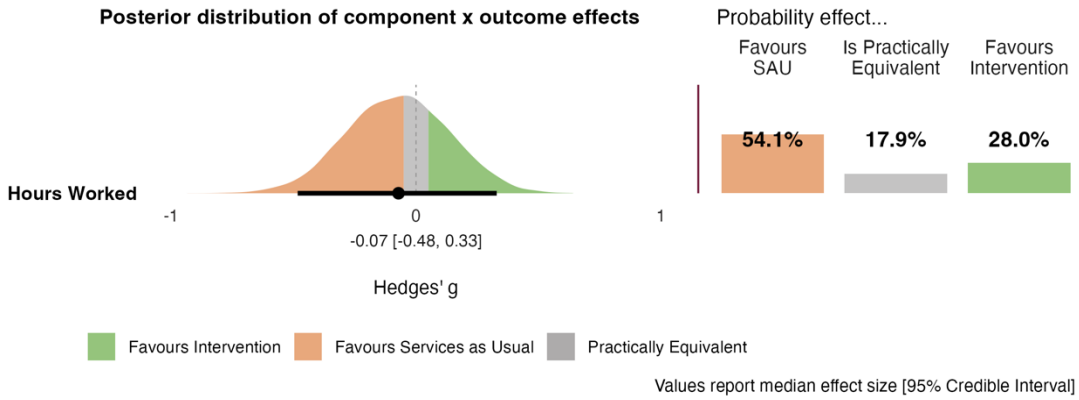


Hours worked

The impact of Unpaid Temporary Work Experience on hours worked is presented in Figure 95.

- The median estimate for Hours Worked falls within the low impact range and favours SAU.
- The probability that the effect favours SAU is greater than half (Pr < 0.05 = 0.54).
- Overall, there is a very low probability that Unpaid Temporary Work Experience has a positive impact on Hours Worked.

Figure 95 Impact of Unpaid Temporary Work Experience on Hours worked



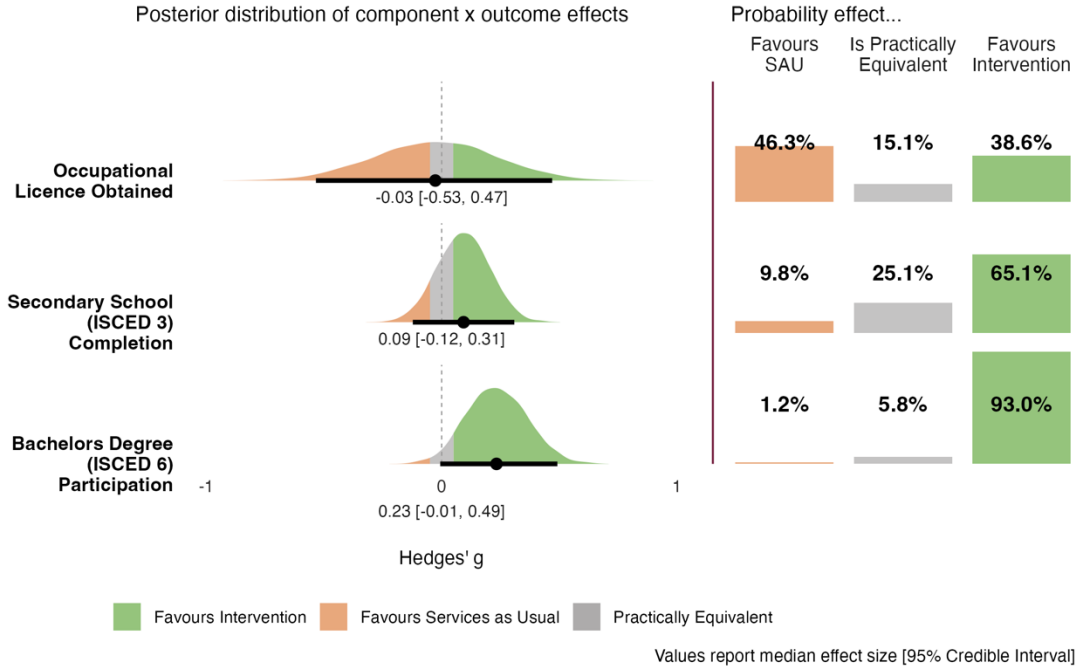
Education and Skills

The impact of Unpaid Temporary Work Experience on education and skills outcomes is presented in Figure 96.Bachelor's degree

- *Occupational licence attainment* — the median estimate falls in the range of little or no impact.
- *Secondary school completion* — the median effect falls within the low impact range (*g*=0.09), with a reasonable chance of an outcome favouring the intervention (Pr > 0.05 = 0.65); however it is more likely to be medium (31%) or low (17%) in magnitude.
- *Bachelor's degree participation* — the median estimate falls in the medium impact range (*g*=0.23). The probability of a positive impact favouring the intervention is high (Pr > 0.05 = 0.93); and is more likely to be high (60%) in magnitude than medium (25%).

Overall, these results suggest that Unpaid Temporary Work Experience can have a positive impact on education and skills outcomes.

Figure 96 Impact of Unpaid Temporary Work Experience on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-

level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of Unpaid Temporary Work Experience between females and males is low in impact: *g*=-0.09, 95% CrI [-0.25, 0.05].
- **Posterior probabilities** — there is a 10.5% chance the impact of Unpaid Temporary Work Experience is higher in all-female study populations and an 89.5% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect for each additional year of mean study age is *g*=0.02 95% CrI [-0.04, 0.08] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.17, 95% CrI [-0.35, 0.63].
- **Posterior probabilities** — there is a 74.5% chance the impact of Unpaid Temporary Work Experience increases with the mean study age.

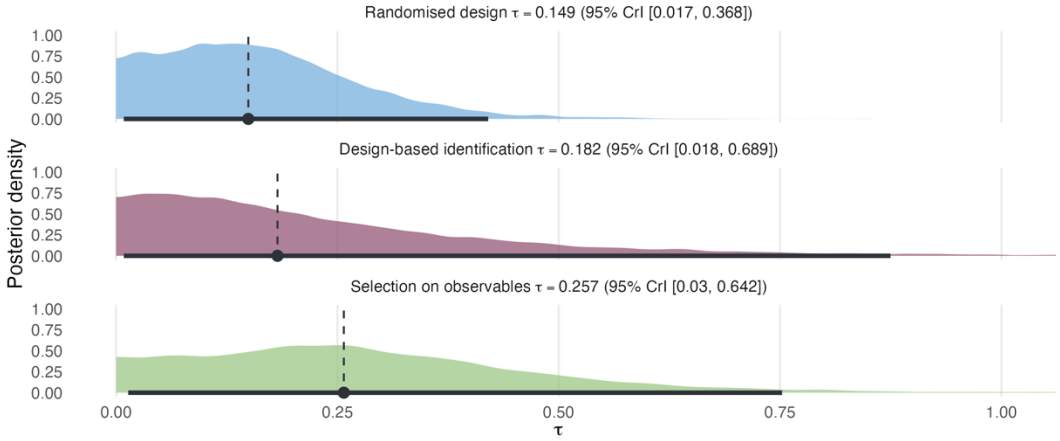
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 97 shows the component-specific heterogeneity by study design. Relative to the overall pattern (Figure 7), heterogeneity is higher across all study designs for Unpaid Temporary Work Experience. This suggests more between-study heterogeneity for this component than in the portfolio overall, especially for SOO. The long upper tails for SOO imply a non-trivial chance of very high heterogeneity.

Figure 97 Posterior distribution of between study heterogeneity (τ) by for Unpaid Temporary Work Experience by study design





Subsidised employment

Meta-analysis results

Wage Subsidies

Key findings

- **Wage subsidies may have small positive effects on current unemployment and NEET status.** Median effects for Currently Unemployed (Pr > 0.05 = 0.54; Pr > 0.20 = 0.13) and Currently NEET (Pr > 0.05 = 0.50; Pr > 0.20 = 0.26) favour the intervention, indicating roughly a one-in-two chance of a positive effect, though impacts are most likely to be low or medium in magnitude.
- **Wage subsidies may improve Secondary School Completion.** There is a high probability of a positive effect (76%), with almost two-thirds of the posterior in the medium- or high-impact range.
- **Impacts may vary by population characteristics.** Effects do not appear to differ meaningfully between all-female and all-male study populations. By contrast, effects are very likely to increase with mean study age (95%), with a large estimated difference between studies with mean ages of 24 versus 16, though this contrast remains uncertain.
- **How to make sense of this.** Wage subsidy schemes are often implemented during periods of high unemployment, when young people face strong competition from older or more qualified or experienced workers. This context may mean that more marginalised populations are served relative to other ALMPs. As with other forms of employment experience, wage subsidies may help young people build employability and social capital that may support longer-term labour market attachment. Positive effects on secondary school completion may reflect programme timing or design features that encourage re-engagement with education, but this mechanism warrants further investigation.

Definition

Wage subsidies are financial incentives provided to employers to support the employment of disadvantaged young jobseekers. The subsidies can take the form of direct payments, tax breaks, reduced payroll taxes, reduced social security contributions, or tax credits. The primary aim is to help individuals secure longer-term employment by reducing the financial risks to employers who perceive disadvantaged young people's productivity will be below market standards. The ultimate goal is to facilitate immediate employment and then encourage sustained employment by

lowering employment costs for employers and enhancing the employability of the jobseeker.

Evidence profile

A summary of the evidence used to inform the analysis of Wage Subsidies is summarised in Table 35. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported.

Table 35 Evidence profile for Wage Subsidies

SUMMARY	COUNT			
Number of studies	17			
Number of effect sizes	34			
Study design	RE: 4	SOO: 11	DBI: 2	
Risk of bias	Acceptable: 9		High: 8	
Study design x risk of bias	Acceptable High	RE: 2 RE: 2	SOO: 6 SOO: 5	DBI: 1 DBI: 1
Studies reporting each outcome:				
Labour Force Status	Currently Employed (n=7); Recent Employment (n=2); Currently Unemployed (n=4); Currently NEET (n=1)			
Employment Compensation	Labour Earnings (n=2); Wages (n=2)			
Employment duration	Period Employed (n=2)			
Hours Worked	Hours Worked (n=2)			
Education & Skills	Secondary School (ISCED 3) Completion (n=22); Apprenticeship Participation (n=1)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Wage Subsidies. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

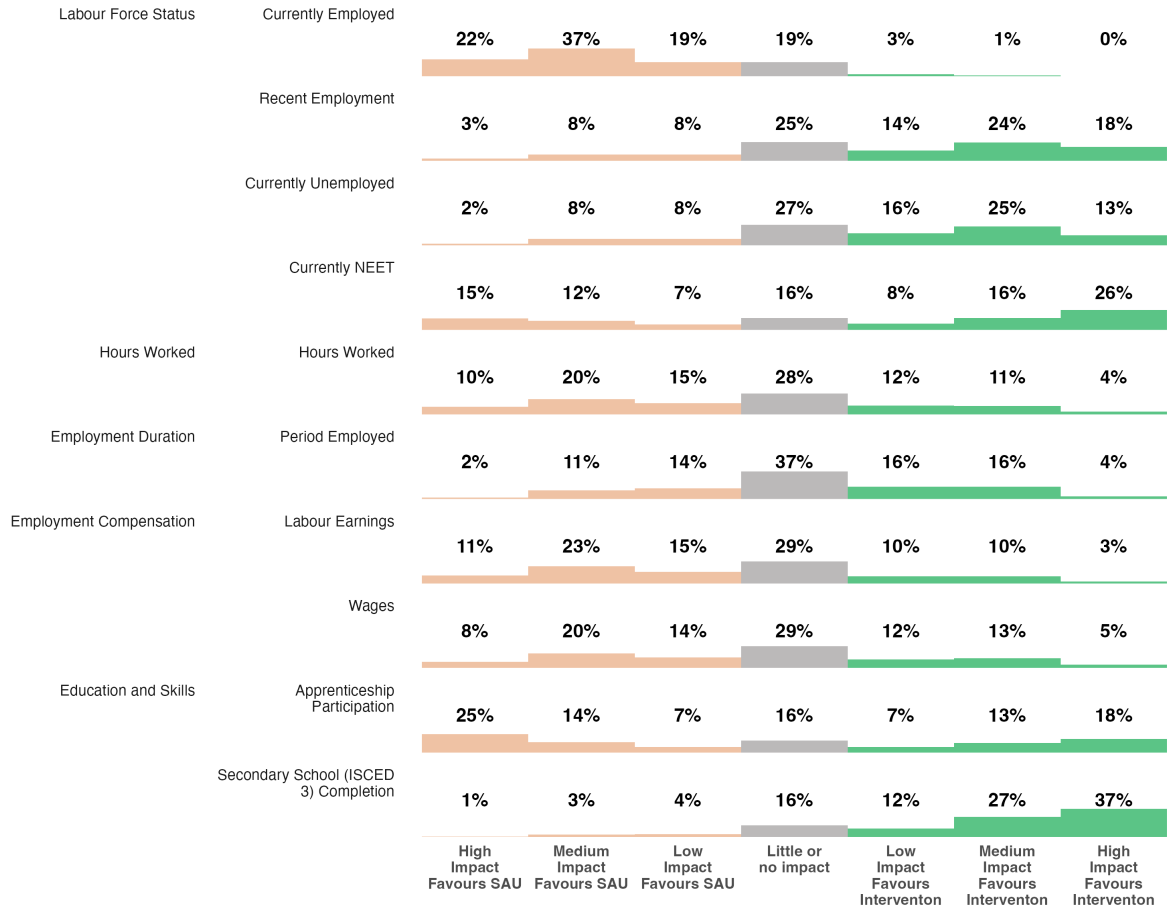
2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 98 shows the posterior probability that the effect of Wage Subsidies on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 98 Probability of the scale of impact of Wage Subsidies



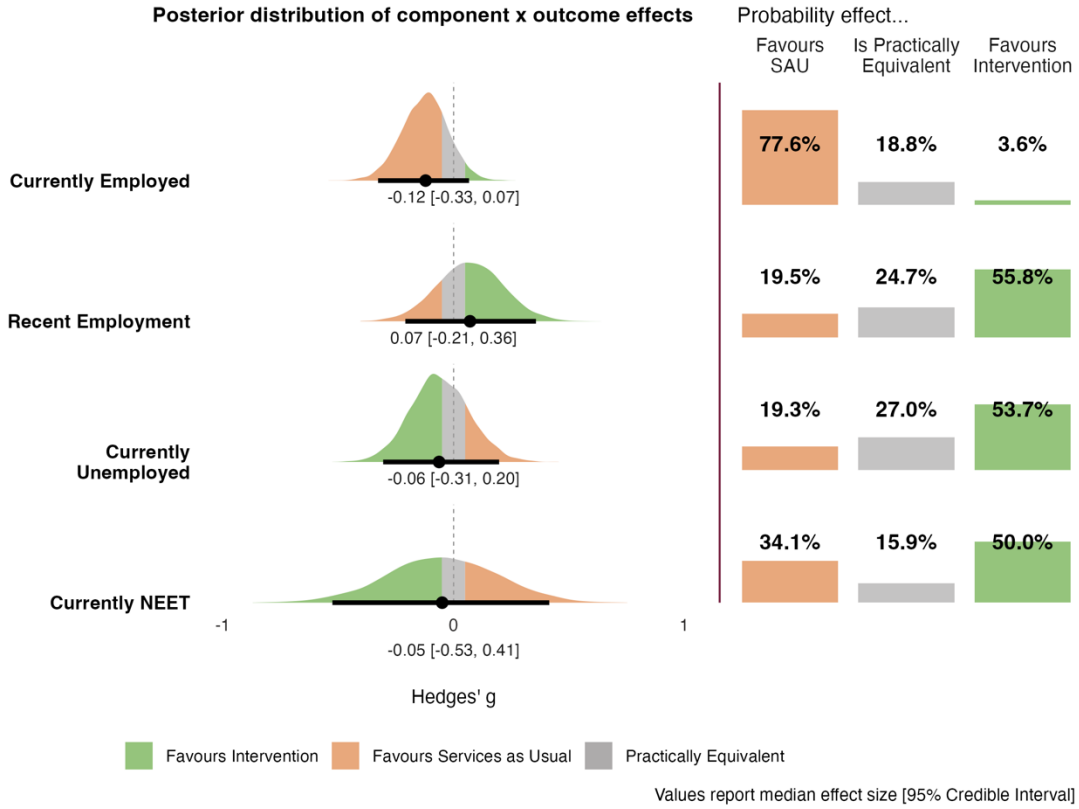
Labour Force status

The impact of Wage Subsidies on labour force outcomes is presented in Figure 99.

- Median estimates for Recent Employment, Currently Unemployed and Currently NEET all favour the intervention and fall within the low impact range. The result for Currently Employed is a medium-sized estimate favouring SAU.
- The probability of any effect favouring the intervention is around even for Recent Employment (Pr > 0.05 = 0.56), Currently Unemployed (Pr > 0.05 = 0.54) and Currently NEET (Pr > 0.05 = 0.50).
- The probability of a medium or high impact is greater than one in three for Recent Employment, Currently Unemployed and Currently NEET.

Overall, these suggest that Wage Subsidies can have a positive effect on Recent Employment, Currently Unemployed and Currently NEET more than half of the time.

Figure 99 Impact of Wage Subsidies on Labour Force status

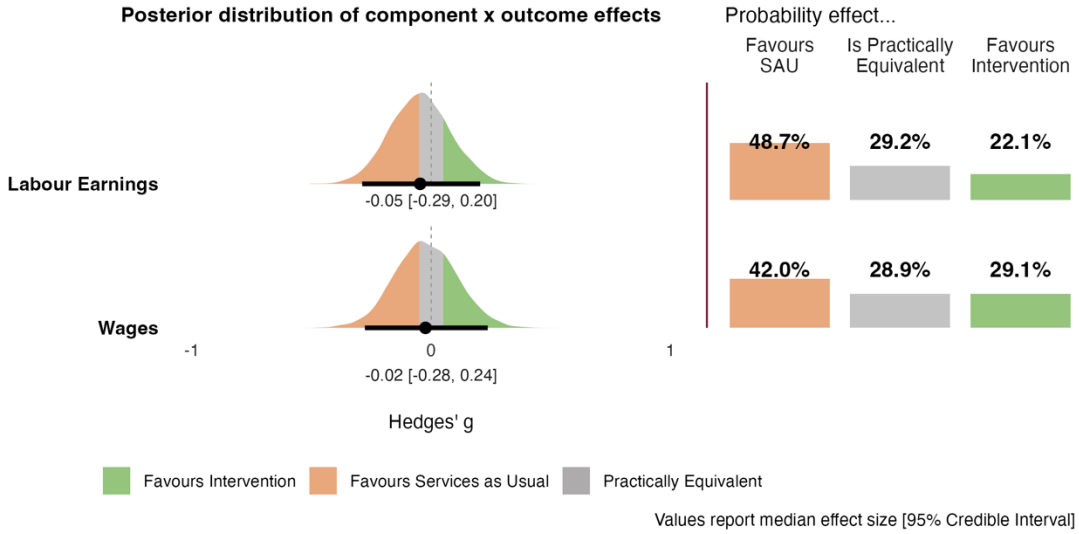


Employment compensation

The impact of Wage Subsidies on employment compensation outcomes is presented in Figure 100.

- Median estimates for Labour Earnings favour SAU, but is low in magnitude. Results for Wages are consistent with little or no effect.
- The probability of any positive impact is low for both outcomes: 29% for Wages and 22% for labour earnings.
- The probability of medium or high impacts is low across both outcomes (<20%).
- Overall, these results suggest little evidence that Wage Subsidies improves employment compensation.

Figure 100 Impact of Wage Subsidies on Employment compensation

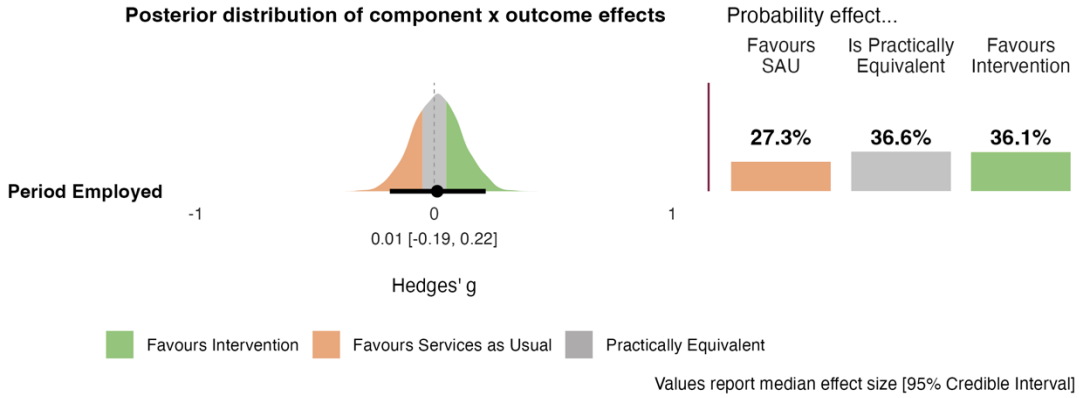


Employment duration

The impact of Wage Subsidies on employment duration outcomes is presented in Figure 101.

- The median estimate for Period Employed is close to zero and falls within the range of little or no effect.
- The probability that the intervention and SAU are practically equivalent is about one-in-three (37%).
- The probability of a medium impact is modest (16%), while a high impact is very unlikely (4%).
- Overall, there is a low probability that Wage Subsidies increases time spent in employment.

Figure 101 Impact of Wage Subsidies on Employment duration

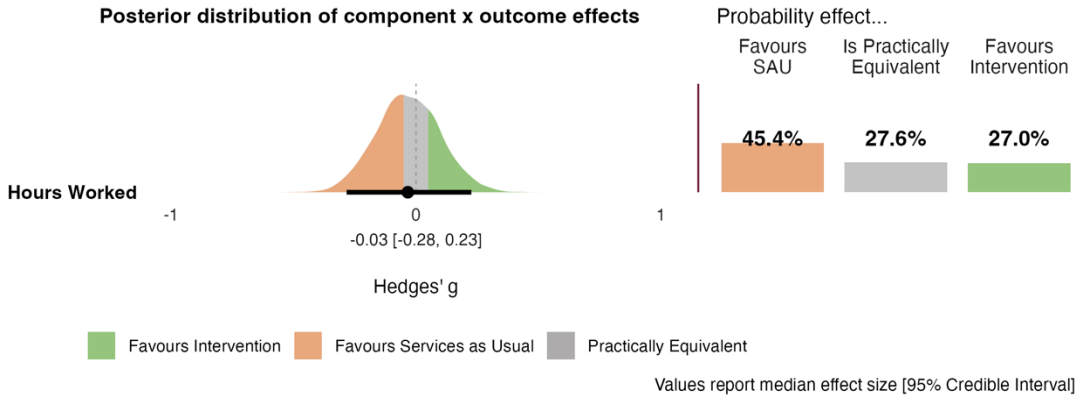


Hours worked

The impact of Wage Subsidies on hours worked is presented in Figure 102.

- The median estimate for Hours Worked falls within the range of little or no effect.
- The probability of any positive impact is just over one-in-four (Pr > 0.05 = 0.27).
- The probability of a medium (11%) or high (4%) impact is low (15%).
- Overall, Wage Subsidies is unlikely to increase hours worked relative to SAU.

Figure 102 Impact of Wage Subsidies on Hours worked



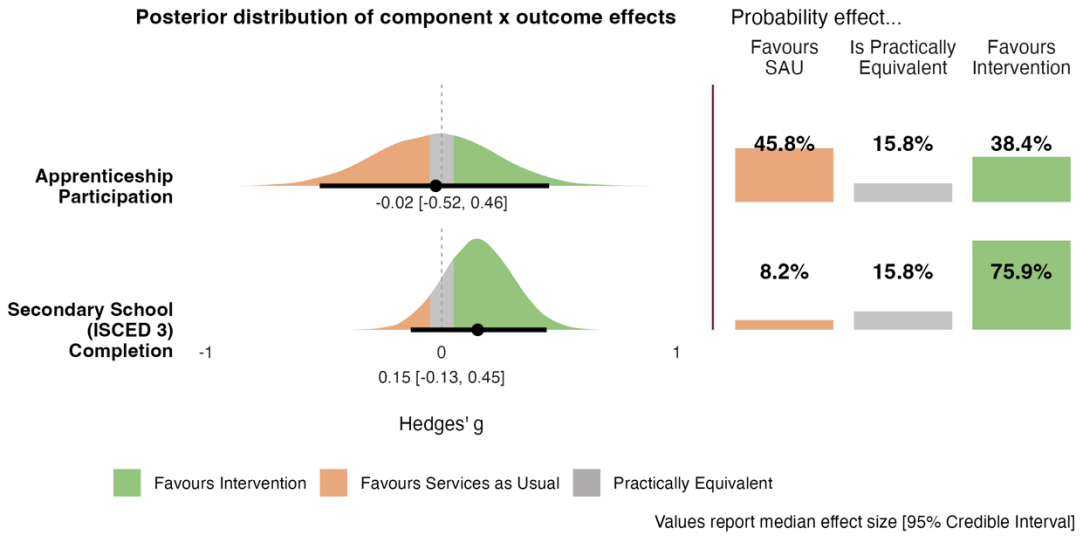
Education and Skills

The impact of Wage Subsidies on education and skills outcomes is presented in Figure 103. Due to a lack of studies reporting these outcomes, only apprenticeship participation and secondary school completion could be examined.

- *Apprenticeship participation* — the median estimate is within the range of little or no effect.
- *Secondary school completion* — the median effect favours the intervention and falls within the medium-sized impact range (*g*=0.15), with an 76% probability of any positive impact. There is almost a two in three chance than the impact is medium (27%) or high (37%).

Overall, Wage Subsidies may meaningfully increase secondary school completion.

Figure 103 Impact of Wage Subsidies on Education and Skills



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of wage subsidies between females and males falls within the little or no impact range: *g*=0.01, 95% CrI [-0.13, 0.15].

- **Posterior probabilities** — there is a 56.9% chance that the impact of wage subsidies is higher in all-female study populations and a 43.1% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect of wage subsidies for each additional year of mean study age is *g*=0.08 95% CrI [-0.01, 0.17] per year.

- **Contrast (24 vs 16)** — the difference in the estimated effect between studies with mean age 24 and 16 is *g*=0.65, 95% CrI [-0.11, 1.34].

- **Posterior probabilities** — there is a 95.4% chance the impact of Wage Subsidies increases with the mean study age.

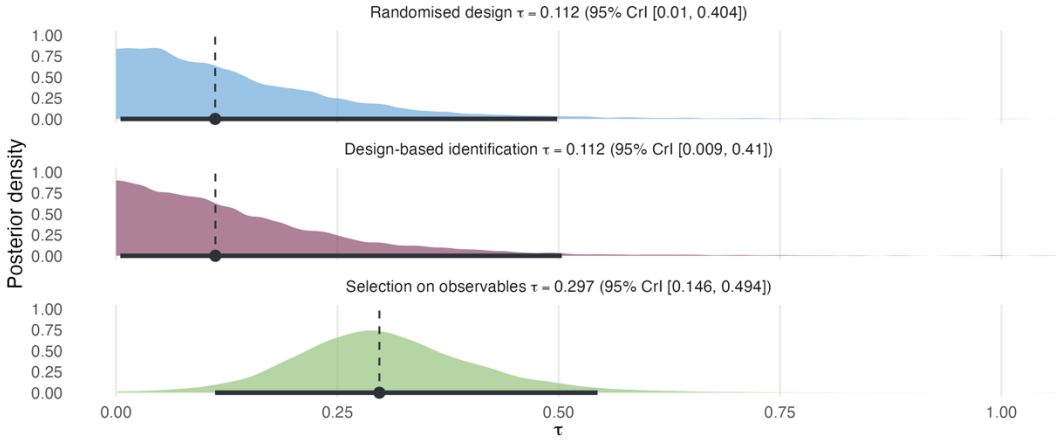
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 104 shows the component-specific heterogeneity (τ) by study design. Relative to the global results (Figure 7), τ is modest in DBI and RE studies, but substantially higher in SOO studies. These results suggest that between-study variation is higher amongst studies that include a wage subsidies component. Furthermore, there is considerable study design dependent variability for this component.

Figure 104 Posterior distribution of between study heterogeneity (τ) by for Wage Subsidies by study design



Public Works

Key findings

- **Outcome coverage is narrow.** Evidence is available for a limited set of outcomes, and findings should therefore be interpreted cautiously.
- **Possible reductions in unemployment.** The median effect on unemployment is medium in size and favours the intervention (Pr > 0.05 = 0.62; Pr > 0.2 = 0.41), indicating roughly even chances that impacts are medium or large in magnitude.
- **Impacts may vary by population, but estimates are uncertain.** Effects are more likely to be larger in all-male than all-female study populations (68%), though the estimated difference falls in the medium range and is imprecisely estimated. Effects are also likely to increase with mean study age (82%), with a large estimated contrast between studies with mean ages of 24 versus 16, albeit with substantial uncertainty.
- **How to make sense of this.** Public works programmes are often deployed during periods of labour market distress and tend to serve highly marginalised groups who have limited access to other forms of work experience. The evidence suggests these programmes may reduce unemployment in such contexts, though impacts appear context-specific and warrant cautious interpretation.

Definition

Public works programmes are government-initiated employment schemes aimed at providing temporary employment through infrastructure development, maintenance, and other community service projects. Public works programmes directly employ individuals through government projects, whereas wage subsidies incentivise private and third sector employers to hire individuals by offsetting some of the employment costs. Public works programmes are often considered a solution in times of crises, when there is not enough labour demand and thus as a temporary safety net.

Evidence profile

A summary of the evidence used to inform the analysis of Public Works is summarised in Table 36. The evidence profile shows how many studies contributed information toward this component, their design and risk of bias, and which outcome domains they reported. Overall, there were few eligible studies for these analyses, with a limited range of outcomes available, and low certainty in the findings presented.

Table 36 Evidence profile for Public Works

SUMMARY	COUNT			
Number of studies	7			
Number of effect sizes	8			
Study design	RE: 1	SOO: 6	DBI: 0	
Risk of bias	Acceptable: 6		High: 1	
Study design x risk of bias	Acceptable High	RE: 0 RE: 1	SOO: 6 SOO: 0	DBI: 0 DBI: 0
Studies reporting each outcome:				
Labour Force Status	Currently Unemployed (n=1)			
Employment Compensation	Wages (n=1)			
Employment duration	Period Employed (n=9)			

Key: RE — Randomised Experiments; SOO — Selection on Observables; DBI — Design-based Identification

Overall component effects

This section presents the overall effects of Public Works. For each outcome, we present the results in a series of figures that show:

1. **Posterior distribution of effect sizes** — the full range of plausible values for Hedges' *g* given the data and model. Areas of the distribution shaded in green indicate posterior mass favouring the intervention component, while those in orange indicate mass favouring SAU. Grey areas reflect the ROPE where the effect is too small to be considered meaningful.

2. **Median and 95% credible interval (CrI)** — the central estimate (black dot) and the interval that contains 95% of the posterior probability. The CrI can be interpreted

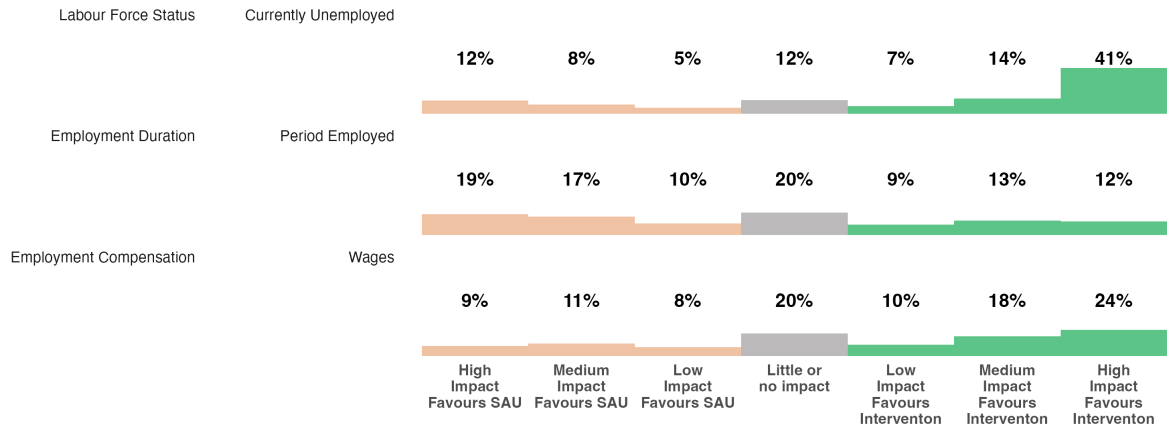
directly as the range within which the effect lies with 95% probability, given the model and data.

3. **Probabilities that the effect favours the intervention, favours SAU, or is negligible** — the posterior probability that the effect exceeds the ROPE in a positive direction, exceeds it in a negative direction, or falls within the ROPE.

4. **Impact magnitude categories** — the probability that the effect falls into one of four impact categories: little or no impact ($|g| < 0.05$), low impact ($0.05 \leq |g| \leq 0.10$), medium impact ($0.10 < |g| \leq 0.20$), or high impact ($|g| > 0.20$) thresholds, based on revised versions of benchmarks used in the first version of the Toolkit.

Figure 105 shows the posterior probability that the effect of Public Works on each outcome falls into one of the defined impact categories, ranging from little or no effect to high impact favouring either the intervention or SAU.

Figure 105 Probability of the scale of impact of Public Works



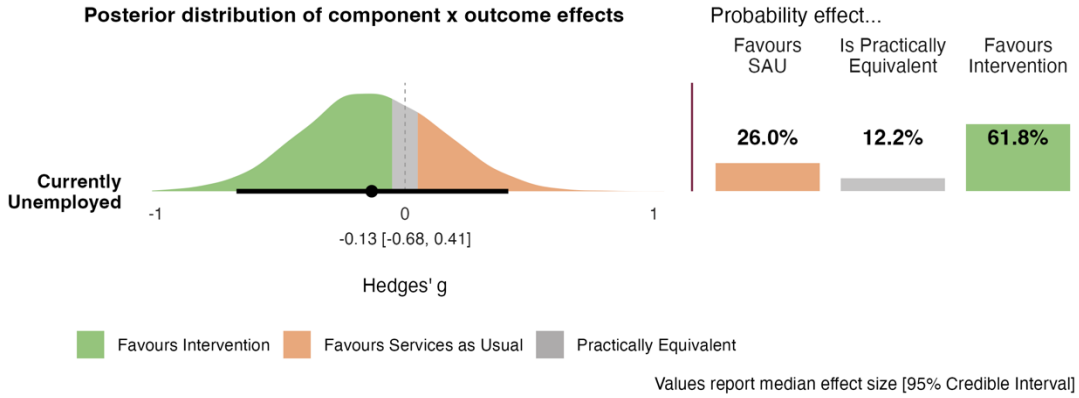
Labour Force status

The impact of Public Works on Currently Unemployed is presented in Figure 106, although it should be noted findings are from a single study.

- The medium-sized median estimate favours the intervention.
- The probability of an effect favouring the intervention is greater than even ($Pr > 0.05 = 0.62$).
- The probability of a medium (14%) or high (41%) impact is greater than 50%.

- Overall, these findings suggest that Public Works can reduce unemployment at 24 months more than half the time.

Figure 106 Impact of Public Works on Labour Force status

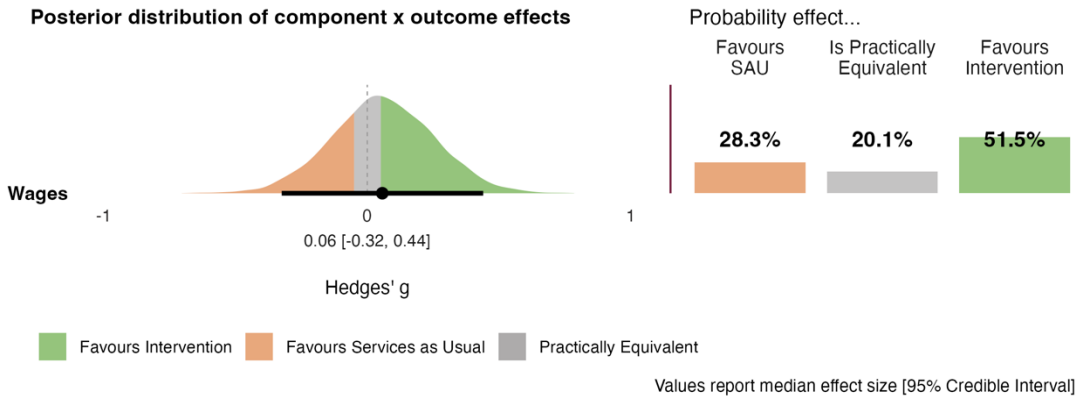


Employment compensation

The impact of Public Works on wages is presented in Figure 107, although it should be noted findings are from a single study.

- The low-magnitude median estimate for Wages favours Public Works.
- The probability of any positive impact is 52%.
- The probability of a medium (18%) or high (24%) impact is less than half (42%).
- Overall, these results suggest the impact of Public Works on Wages is unclear.

Figure 107 Impact of Public Works on Employment compensation

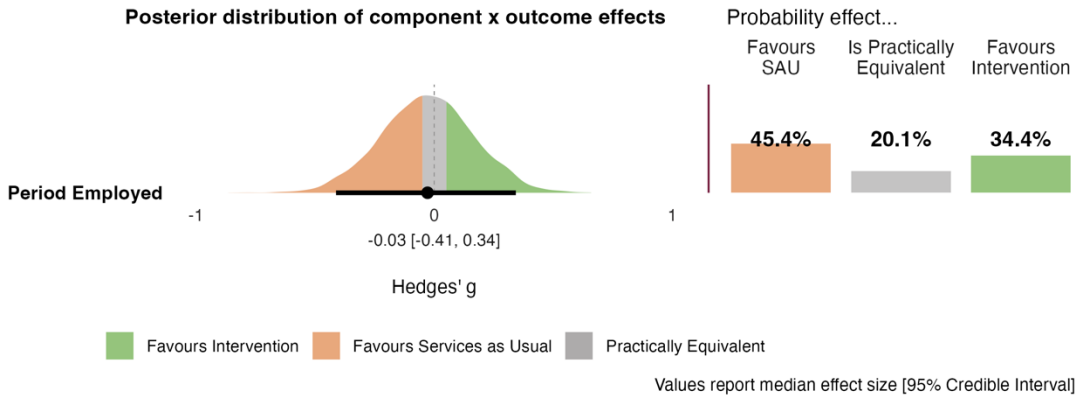


Employment duration

The impact of Public Works on employment duration outcomes is presented in **Figure 108**.

- The median estimate for Period Employed falls within the little or no impact range.
- The probability of any positive impact is 34%.
- Overall, Public Works does not appear likely to increase Period Employed at 24 months relative to SAU.

Figure 108 Impact of Public Works on Employment duration



Component effects by sex

To assess subgroup effects by sex, for each outcome, we predicted effects when the proportion of females in the study population is set to 0 (all-male) and to 1 (all-female). Because the model estimates a single, component-specific moderation effect that applies across all outcomes, any sex differences should be understood as component-level patterns rather than outcome-specific effects. Accordingly, we report one overall contrast (female-male) where positive values indicate larger effects in all-female studies.

- **Contrast** — the difference in the estimated effect of public works between females and males is falls within the medium impact range: *g*=- 0.115, 95% CrI [-0.58, 0.35].
- **Posterior probabilities** — there is a 31.7% chance the impact of public works is higher in all-female study populations and a 68.3% chance that they are larger in all-male ones.

As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so the contrasts reflect study-level associations rather than individual-level causal moderation and may be confounded by unmeasured contextual or implementation factors.

Detailed results showing the estimated effects by sex for each outcome x component combination are included in Appendix B.

Component effects by age

To assess subgroup effects by age, for each outcome, we predicted effects at different values of the study's mean age while holding other variables constant. Because the model estimates a single, component-specific linear age effect that applies across all outcomes, any age differences should be understood as component-level patterns, not outcome-specific effects. Accordingly, here we report both an age gradient (per year) and a contrast comparing studies with a mean age 24 vs 16.

- **Age gradient** — the change in the estimated effect of public works for each additional year of mean study age is *g*=0.08 95% CrI [-0.10, 0.25] per year.
- **Contrast (24 vs 16)** — the difference in the estimated effect of public works between studies with mean age 24 and 16 is *g*=0.65, 95% CrI [-0.80, 2.03].
- **Posterior probabilities** — there is an 82.3% chance the impact of public works increases with the mean study age.

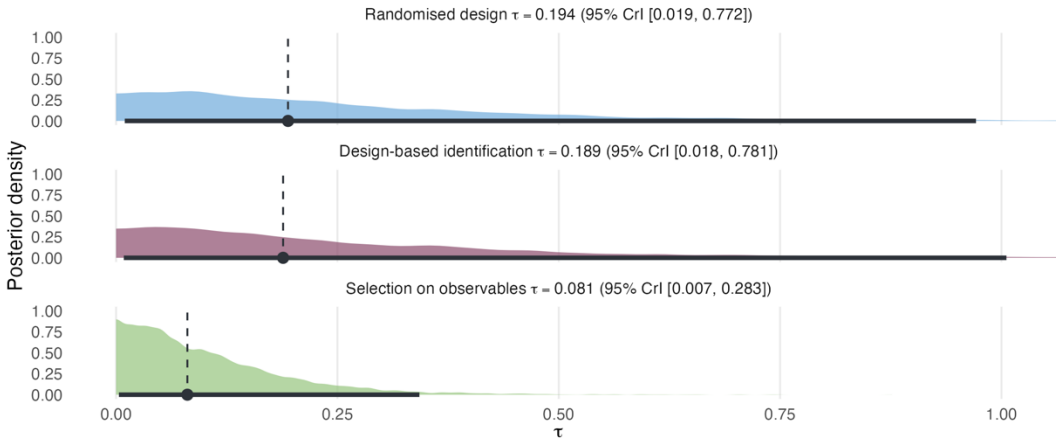
As noted in the methodology section, these subgroup estimates should be interpreted with caution. The unit of analysis is the study, so they reflect study-level associations rather than individual-level causal moderation. They also assume a linear age relationship over this range and could be confounded by unmeasured contextual or implementation factors.

Detailed results by age for each outcome x component combination—with predicted effects at selected ages (16, 18, 20, 22, and 24 years)— are provided in Appendix C.

Component-level heterogeneity

Figure 109 shows the component-specific heterogeneity by study design. The results vary from the global distributions, with RE showing a high median value of τ with a long tail. Result for SOO are smaller than its global distribution (Figure 7). This suggests greater between-study variability among the more rigorously identified studies for public works. However, there is only one RE contributing to this component, so the RE distribution is based on limited information and should be interpreted cautiously.

Figure 109 Posterior distribution of between study heterogeneity (τ) by for Public Works by study design





Discussion

Discussion

This review synthesised evidence on active labour market programmes (ALMPs) for young people in high income countries. Using a multivariate hierarchical Bayesian component network meta-analysis, we estimated the impact of individual intervention components on outcomes spanning labour market participation, employment compensation, period employed and education and skills, relative to services as usual. Rather than comparing bundled interventions, the analysis decomposed programmes into their constituent components, allowing estimation of the contribution of different forms of skills development, employment services, employment experience, , subsidised employment, and self-employment support. This approach provides a component-level assessment on which elements of ALMPs are more, or less, effective at improving outcomes for young people relative to services as usual.

Summary of key findings

Reporting of findings using the Bayesian CNMA approach differs from more conventional assessments of effectiveness using significance testing. Instead, results are reported as: i)) the posterior probability that the effect lies outside the region of practical significance (either favouring the intervention or SAU); ii) the posterior probability that the effect exceeds thresholds corresponding to small, medium or large impacts, aligning with scales used in the YFF Toolkit. Given that all studies are included and that information from indirect comparisons is included in calculations, it is likely these estimates will be more generalisable to the overall population of relevant studies than a conventional frequentist approach would be.

Employment outcomes

A small number of components showed a very high posterior probability (>0.90) of a meaningful effect ($g > 0.05$) favouring the intervention on specific employment outcomes. These included paid temporary work experience, which was highly likely to reduce current unemployment (96%), and unpaid temporary work experience, which showed a very high probability of increasing current employment (approximately 100%) and reducing NEET status (96%). Employment coaching also showed a very high probability of reducing NEET (95.8%).

Several additional components demonstrated a high posterior probability (>0.80) of meaningful effects on employment-related outcomes. Job-specific technical skills delivered through on-the-job training were highly likely to improve labour earnings (96%) and wages (84%). Self-employment support showed a very high probability of increasing

self-employment (100%) alongside a very high probability of reducing unemployment (100%). Soft skills training showed a high probability of improving wages (86%), and financial assistance showed a high probability of improving recent employment (83%).

Education and skills outcomes

Several components showed a very high posterior probability (>0.90) of a meaningful effect favouring the intervention on education and skills–related outcomes. Behavioural skills training demonstrated a very high probability of improving both secondary school completion (approximately 100%) and bachelor's degree participation (approximately 100%). Job-specific technical skills delivered through off-the-job training also showed a very high probability of improving secondary school completion (94%). Job search assistance was highly likely to increase bachelor's degree participation (99%). In addition, unpaid temporary work experience showed a very high probability of increasing bachelor's degree participation (93%).

A smaller number of components showed a high posterior probability (>0.80) of meaningful effects. Paid temporary work experience showed a high probability of increasing bachelor's degree participation (87%), while job search preparation showed a high probability of reducing NEET status (85%).

Subgroup effects

Only a small number of subgroup contrasts showed meaningful variation ($|g| > 0.05$), indicating potentially meaningful differences in component effects across populations.

By sex, basic skills training showed larger estimated effects in all-female study populations, with a 97% posterior probability that effects are larger for females. In contrast, behavioural skills training and job-specific technical skills delivered off-the-job showed larger estimated effects in all-male study populations, each with a 98% posterior probability favouring males. While several other sex-based contrasts showed high directional probabilities, the magnitude of these differences was not meaningful ($|g| < 0.05$).

By age, several components showed larger estimated effects in studies with older participants when comparing mean ages of 24 versus 16 years. Soft skills training and job-specific technical skills delivered off-the-job showed high posterior probabilities that effects increase with age (85% and 91%, respectively). Larger estimated effects among older participants were also observed for self-employment support (76%), wage subsidies (95%), and public works (82%). No components showed meaningful contrasts indicating larger effects among younger study populations. Although several components

exhibited high directional probabilities, age-related contrasts were often estimated with substantial uncertainty.

Interpretation

The evidence for off-the-job training is mixed, consistent with wider evidence on the effectiveness of this form of training within ALMPs. The analysis shows an increase in unemployment alongside a reduction in NEET. This pattern may indicate a lock-in effect, whereby participation in off-the-job training temporarily delays or displaces labour market participation until training is completed, although the duration of training is not judged to be particularly long. The reduction in NEET may also reflect the classification of training as a recognised activity within the NEET definition (not in employment, education or training).

There is very limited evidence on self-employment support in ALMPs in high income countries. Based on 5 studies, this analysis suggests that self-employment support has a large impact on self-employment as an outcome, alongside reductions in unemployment and regular employment. The observed interaction with secondary school completion may warrant further investigation to better understand how well secondary education pathways align with the needs of young people engaging in self-employment support.

Evidence on different forms of work experience (including paid and unpaid temporary work experience, wage subsidies and public works) is also mixed. It is unclear what is driving the very high probability of unpaid temporary work experience increasing current employment, this warrants further investigation. Evidence on public works is sparse, and estimated effects are correspondingly uncertain. In contrast, there is more consistent evidence that paid work experience reduces unemployment and wage subsidies improves employment within the last 12 months. Differences in estimated effects across forms of work experience may reflect variation in how these components are implemented and/or combined with other supports, rather than intrinsic differences between paid, unpaid, or subsidised placements. Factors such as programme duration and intensity, and the broader policy and labour market context in which these components are delivered may be important drivers of observed differences and warrant further investigation.

Implications for policy, practice and research Implications for policy, practice, and research from this meta-analysis must be interpreted in light of its broad scope and analytic focus. The component-based approach and subgroup analyses by age and sex allow identification of general patterns, but the heterogeneity of interventions,

populations, and implementation contexts limits the extent to which findings can be translated into context-specific recommendations.

Implications for policy and practice

Several findings have implications for policy and practice, but these should be interpreted cautiously. Age-related patterns suggest that some components (particularly soft skills training (essential skills), off-the-job training, and employment counselling)tend to have larger estimated effects in studies with a higher mean age. However, further exploration of age-related variation is recommended. These findings highlight the potential relevance of training and counselling components within ALMPs, without implying prescriptive guidance on age-specific delivery.

Work experience components, specifically paid work experience, show favourable effects across multiple labour market outcomes, including reductions in NEET status and unemployment and increases in employment. Given the consistency of these effects, paid work experience may be a suitable component to include routinely within ALMPs, where it can support transitions into work and the development of employability. Evidence for wage subsidies is weaker and more uncertain, however these may play a role in facilitating job creation and expanding access to paid work experience during periods of elevated youth unemployment or inactivity.

Implications for research

As with any meta-analysis, the conclusions that can be drawn are constrained by the detail and consistency of reporting in the primary studies. Improving the quality and scope of reporting can strengthen future evidence syntheses. Accordingly, our recommendations focus on this.

First, more impact evaluations would benefit from collecting outcomes over longer time horizons and across a broader range of domains. While employment and education outcomes dominate the existing evidence base, there is limited reporting on wider outcomes that can facilitate or hinder employment such as health, wellbeing, or housing instability. In addition, greater attention should be paid to employment quality as an outcome construct. Beyond whether young people are employed, there is a need to define and measure aspects such as job security and stability, contract type, and job satisfaction.

Second, more detailed reporting of participant characteristics is needed to support moderation analysis. Moving beyond basic demographics, studies should report markers of vulnerability and disadvantage, including prior involvement with child welfare, justice, or homelessness systems, and the presence of a disability. Improved reporting in these

areas would support more informative analyses of heterogeneity across study populations.

Third, clearer and more detailed descriptions of interventions are essential. Primary studies should report what participants received, the intensity of delivery, duration, and how the intervention interacts with other systems such as welfare, education or training. Such detail is critical for understanding how implementation features may influence effectiveness.

Fourth, the evidence does not throw a strong spotlight on the quality of work young people attain short or longer term. Given it is good work that has positive benefits for health and wellbeing and lifetime economic and social outcomes increasing a focus on this in future evaluations of employment and skills interventions would enrich insights into supporting young people into sustainable, meaningful and rewarding employment outcomes.

Finally, greater clarity is required surrounding what SAU involves. What constitutes SAU varies substantially across context and populations and is often poorly described. Future evaluations comparing interventions to SAU should report what comparison-group participants actually received. An alternative approach is to prioritise effectiveness studies that directly compare different ALMP configurations.

Strengths and limitations

Strengths and limitations of Bayesian CNMA

A key strength of our Bayesian CNMA is its ability to estimate component-level effects across multiple outcomes within a single coherent modelling framework. By modelling outcomes and intervention components jointly, the analysis allows information to be shared across outcomes and across intervention comparisons, including indirect evidence. This increases the connectivity of the network and supports more stable and coherent estimation than would be obtained from analysing outcomes or comparisons separately.

The Bayesian framework also facilitates direct probabilistic interpretation of results. Reporting posterior probabilities of effects exceeding thresholds of practical relevance allows uncertainty and effect magnitude to be expressed in a way that is more informative than binary significance testing, particularly in settings with heterogeneous interventions and outcomes.

At the same time, the approach has important limitations. Component-level estimates rely on assumptions about additivity and exchangeability, and their interpretation depends on the adequacy of component definitions and coding. Where components are poorly defined, infrequently observed, or highly correlated with other components, estimates may be imprecise and sensitive to modelling assumptions. In addition, while probabilistic summaries can be informative, they can be challenging to communicate clearly and require careful translation to avoid over-interpretation.

Strengths and limitations of a rapid review methodology

The review adopted a rapid evidence assessment (REA) approach to identify, screen and extract data from studies in response to time and resource constraints. A key strength is that the REA utilised the results of recent evidence synthesis work that undertook comprehensive searches (Apunyo *et al.*, 2022; Puerto *et al.*, 2022). While we have confidence in the methods employed by these authors and reliance on these credible sources created efficiencies, it also represents a limitation, as we were unable to validate their search results or study selection criteria. We sought to mitigate this by undertaking a supplementary grey literature search.

The review was restricted to studies conducted in high-income countries. While a broader scope including low- and middle-income countries would have been more inclusive, this restriction was a pragmatic choice to enhance applicability to the UK policy context and to limit heterogeneity arising from substantially different labour market and institutional settings.

Several methodological compromises typical of REAs also apply. Data extraction and quality assessment were undertaken by a single reviewer, with accuracy checks by an experienced reviewer, but this is not as rigorous as independent double data extraction. This review is subject to the currency and accuracy risks common to all REAs and systematic reviews (Simmonds *et al.*, 2022). Although it reflects the evidence published during the search window, it will lose currency as new studies emerge. Living Systematic Reviews (LSR) are increasingly used to address these currency and accuracy risks (Elliott *et al.*, 2014, 2017). The CNMA framework used in this review provides a strong foundation for future updating and could support a transition to a living approach, allowing findings to be refreshed more efficiently than would be possible using standard REA or systematic review methods.

Strengths and limitations of available evidence

This review draws on a large and growing body of evidence evaluating ALMPs for young people, which continues to expand and suggests scope for future updates and

refinement of this analysis. Overall, study quality was acceptable: only a minority of randomised studies were assessed has having a high risk of bias, while risk of bias for quasi-experimental designs was more mixed. Continued efforts to strengthen the quality of evidence on ALMPs therefore remain important.

At the same time, coverage across components was uneven. Some components—notably self-employment support and public works—were evaluated in only a small number of studies, limiting the ability to draw firm conclusions. Considerable effort was made to codify services as usual into specific intervention components. While this strengthened the connectivity of the network, descriptions of comparison conditions were often minimal, making consistent classification challenging. In addition, component definitions, particularly within employment services, are nuanced, which further complicates accurate coding. The evidence base also remains concentrated in the United States, raising questions about transferability to other contexts. Addressing these gaps will require further high-quality evaluations in a wider range of settings, alongside clearer specification and reporting of interventions.

Limitations in the reporting of results

Time and resource constraints limited the extent to which additional diagnostic and sensitivity analyses could be undertaken and reported. Some key modelling assumptions were not formally interrogated. In particular, we did not assess transitivity or inconsistency within the network, nor did we test the additivity assumption by fitting fully interacting models or exploring potential interaction effects between components.

These limitations mean that results should be interpreted under the assumed model structure. Although these assumptions are standard, untested violations of additivity or inconsistency could affect the magnitude and interpretation of some component estimates. Addressing these issues would require additional modelling and reporting, which was not feasible within the scope of this review.

Conclusion

This review provides a component-level synthesis of the evidence on ALMP for young people in high-income countries. It expands the scope of the YFF youth employment toolkit to encompass 15 intervention components across seven outcomes associated with youth employment, labour market and education participation. Using a Bayesian framework, the analysis provides a probabilistic assessment of which intervention components are more or less likely to produce practically meaningful effects. The findings can be used to inform the design and refinement of programmes aimed at improving labour market outcomes for marginalised young people.

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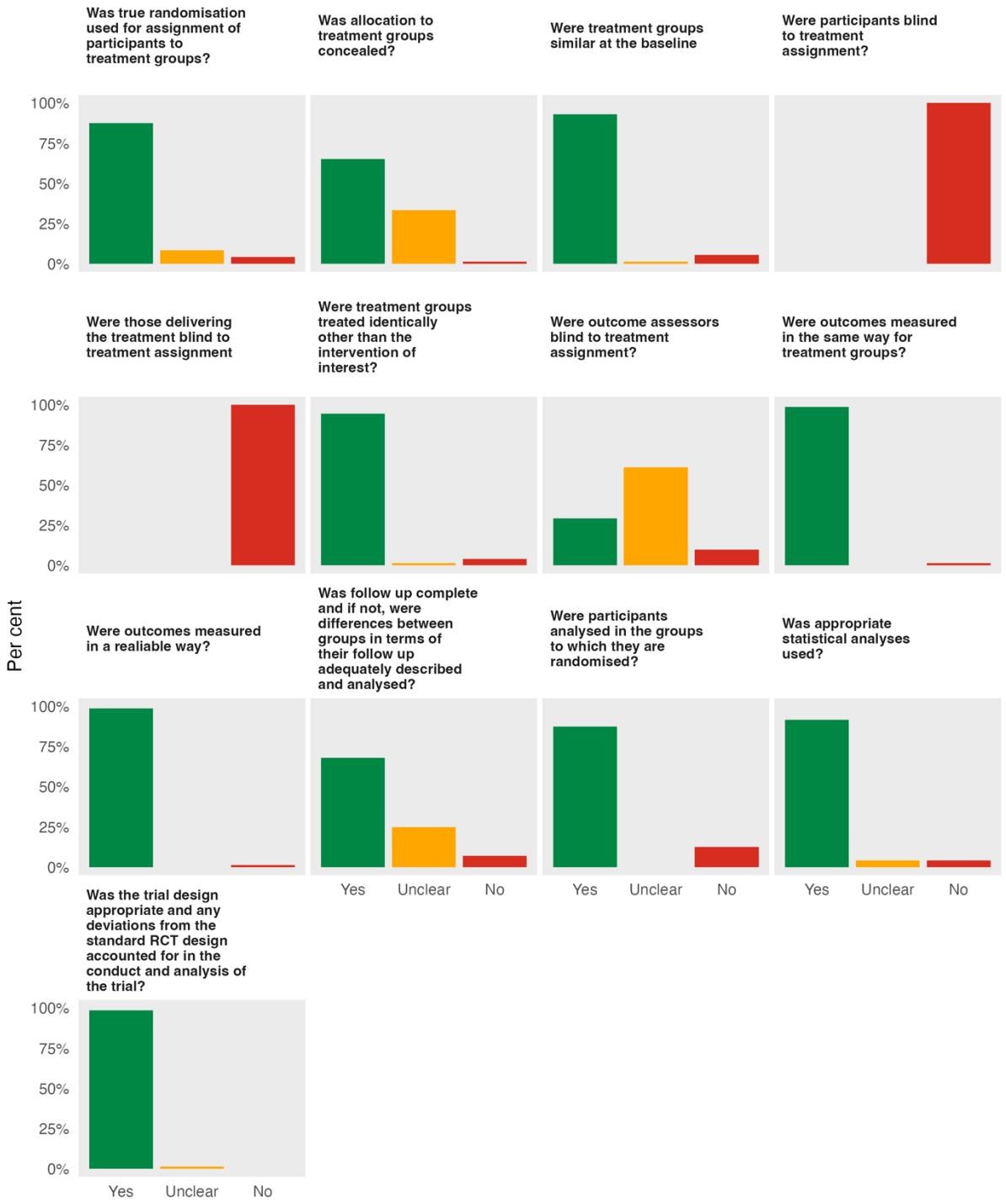
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Appendix A Risk of bias

Figure 110 Distribution of results by question for JBI critical appraisal tool for quasi-experimental studies



Figure 111 Distribution of results by question for JBI critical appraisal tool for randomised studies



Appendix B Subgroup analysis by sex

This appendix presents the detailed results of subgroup effects by sex. For each component x outcome combination, we show predicted effects when the proportion of females in the study sample is set to 0 (all-male sample) and to 1 (all-female sample). Each figure displays:

1. **Posterior distributions of effect sizes** — as with the main effects results, this shows the full range of plausible values for Hedges' *g*. Green shading indicates effects favouring the intervention component, while grey indicates effects favouring services as usual.
2. **Median and 95% CrI** — the central estimate (black dot) and the interval that contains 95% of the posterior probability.
3. **Sex contrasts** — the difference between predicted effects in all-female versus all-male samples. **Mustard** shading indicates contrasts that favour females, while **maroon** shading indicates contrasts that favour males.

As we flagged in the methodology, these subgroup estimates should be interpreted with caution. Because the unit of analysis is the study, the contrasts reflect study-level associations rather than individual-level causal moderation. In other words, these are observational results, not causal effects. Interventions delivered to predominantly male or female populations may differ in many ways beyond sex, and the apparent differences we observe could be confounded by unmeasured contextual or implementation factors. Moreover, the model estimates a single component-specific moderation effect that applies across all outcomes, so observed sex differences should be understood as component-level patterns rather than outcome-specific effects.

Basic Skills Training

Figure 112 Impact of Basic Skills Training on Labour Force status

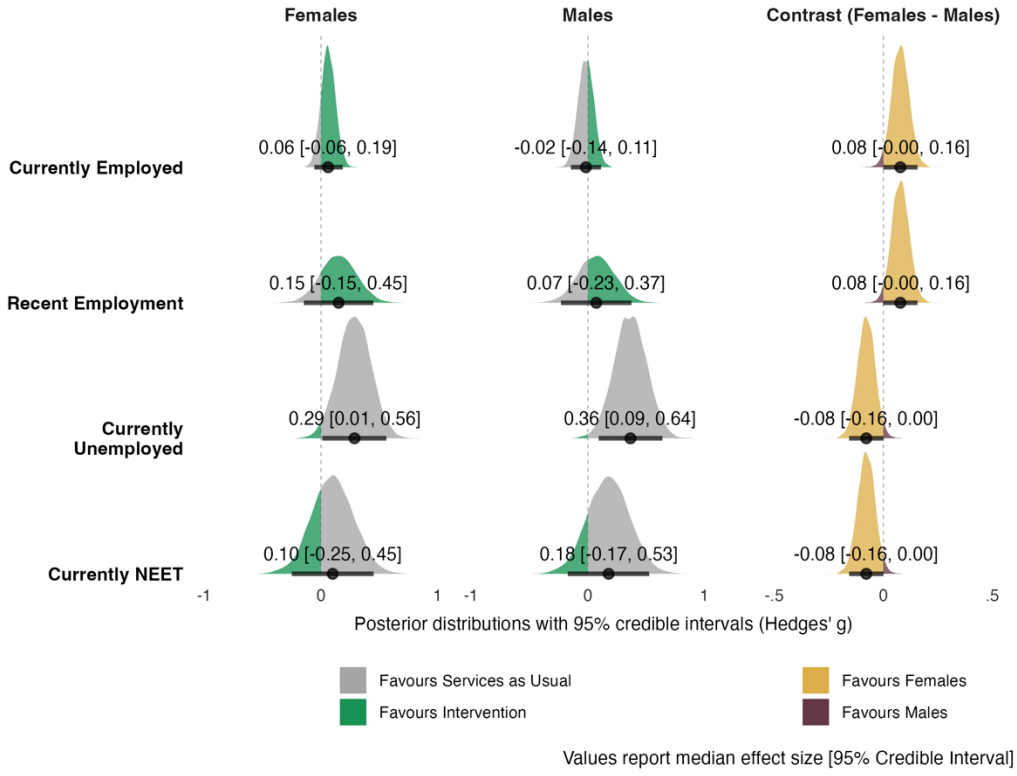


Figure 113 Impact of Basic Skills Training on Employment compensation

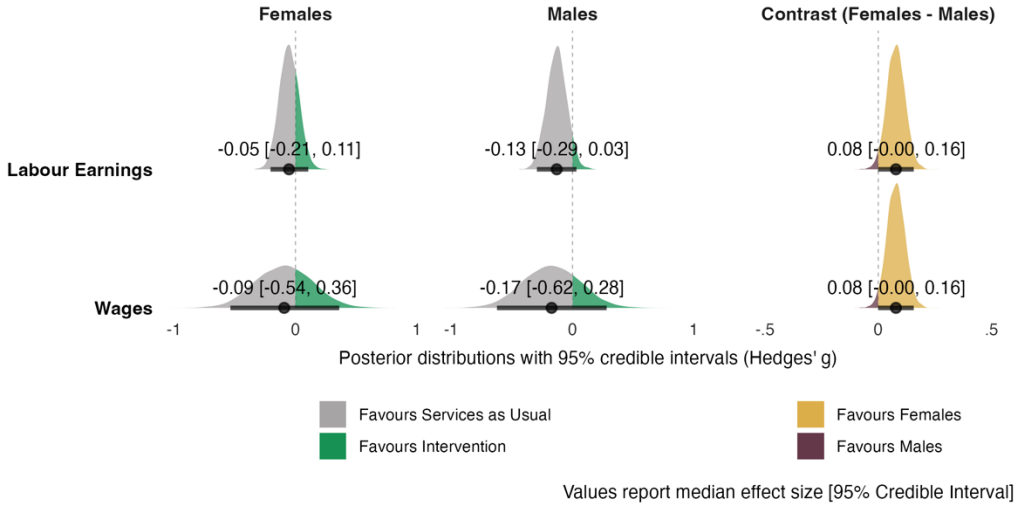


Figure 114 Impact of Basic Skills Training on Employment duration

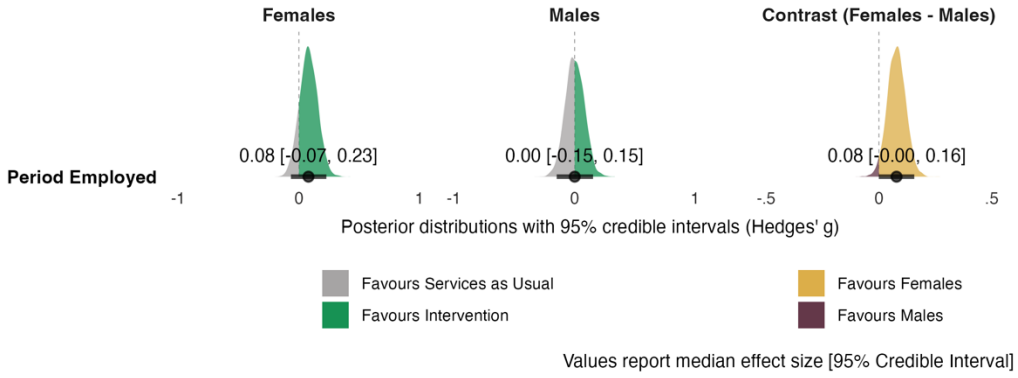


Figure 115 Impact of Basic Skills Training on Hours worked

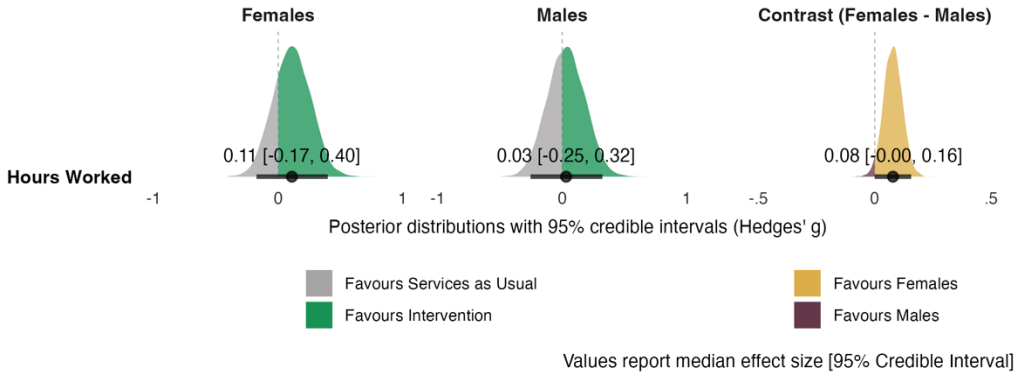
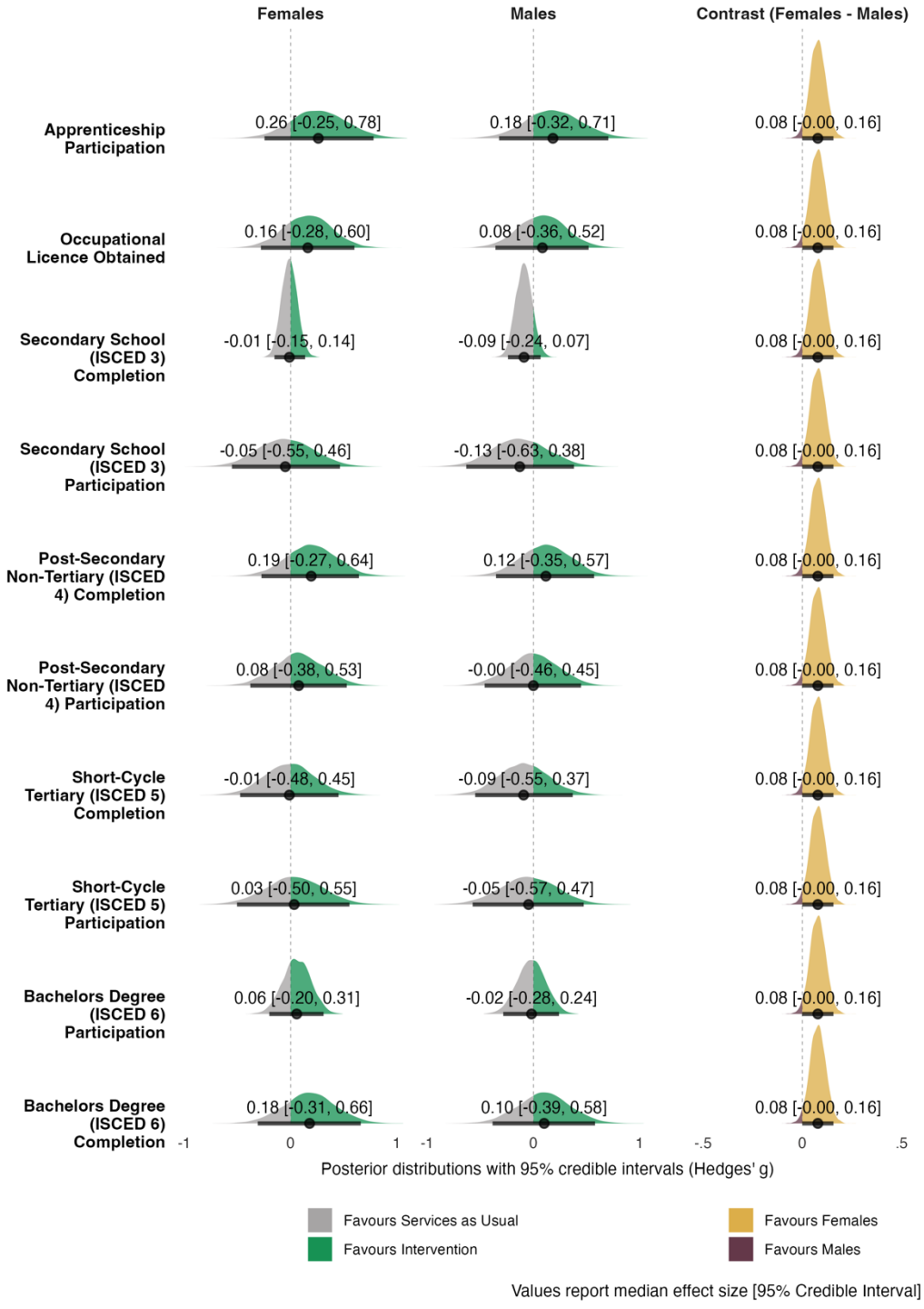


Figure 116 Impact of Basic Skills Training on Education and Skills



Soft Skills Training

Figure 117 Impact of Soft Skills Training on Labour Force status

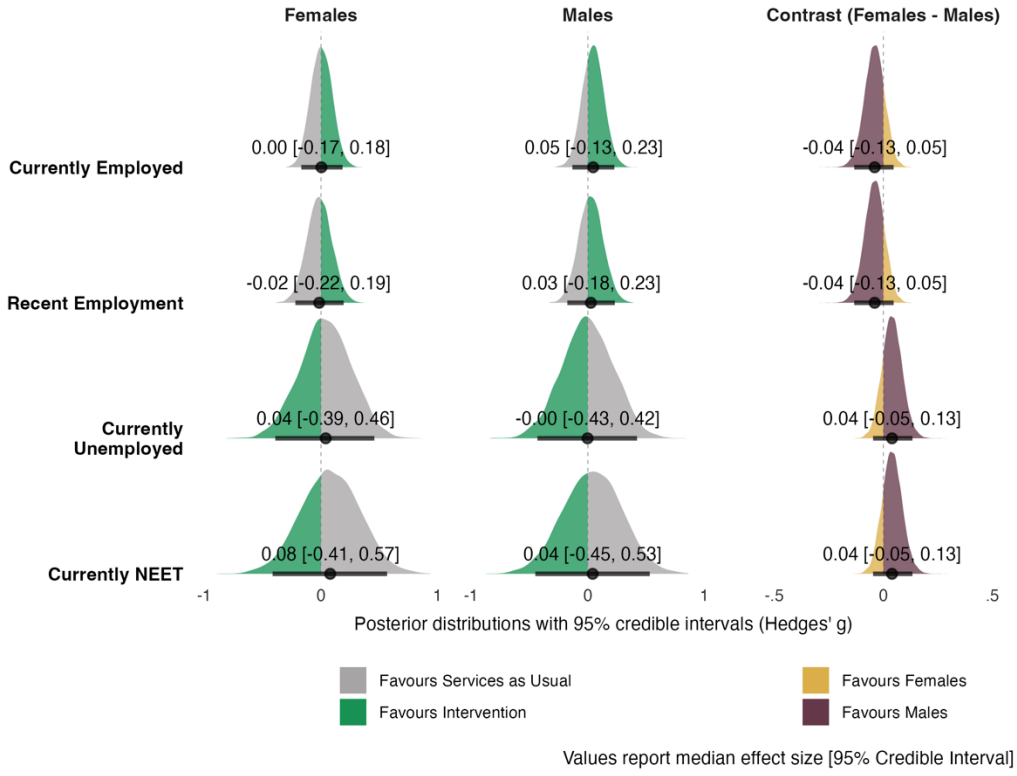


Figure 118 Impact of Soft Skills Training on Employment compensation

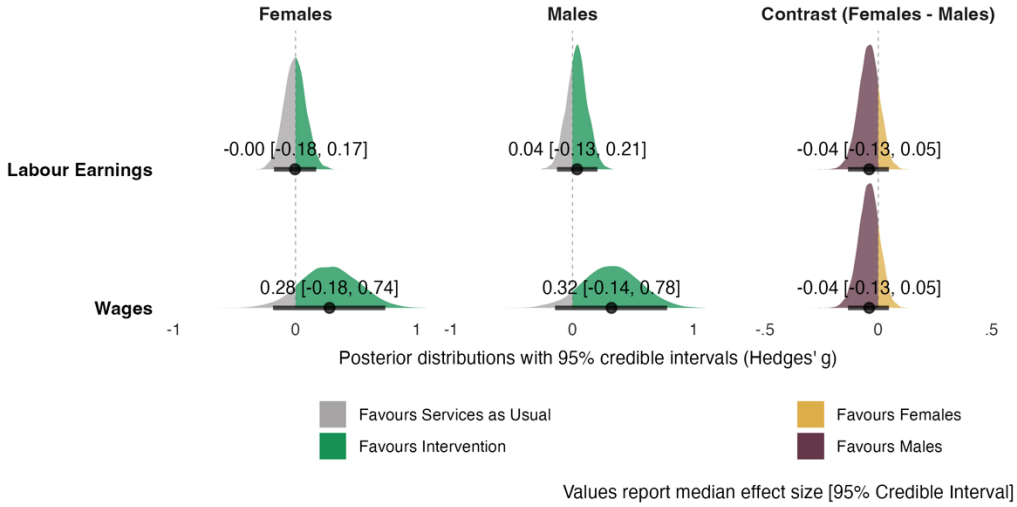


Figure 119 Impact of Soft Skills Training on Employment duration

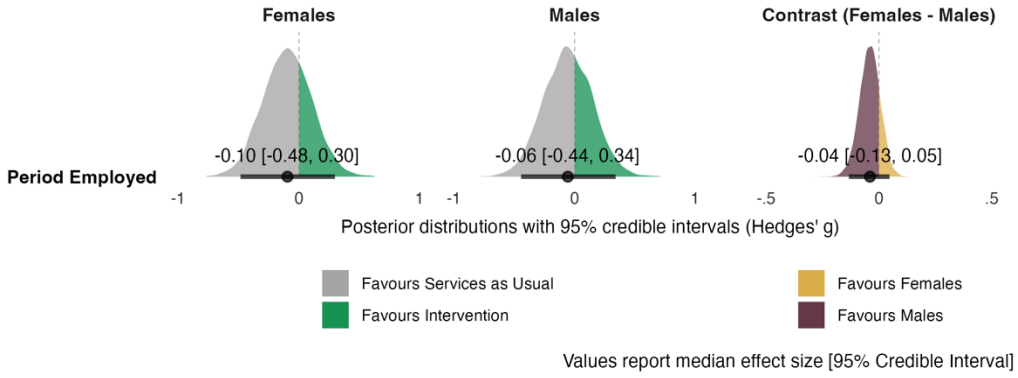


Figure 120 Impact of Soft Skills Training on Hours worked

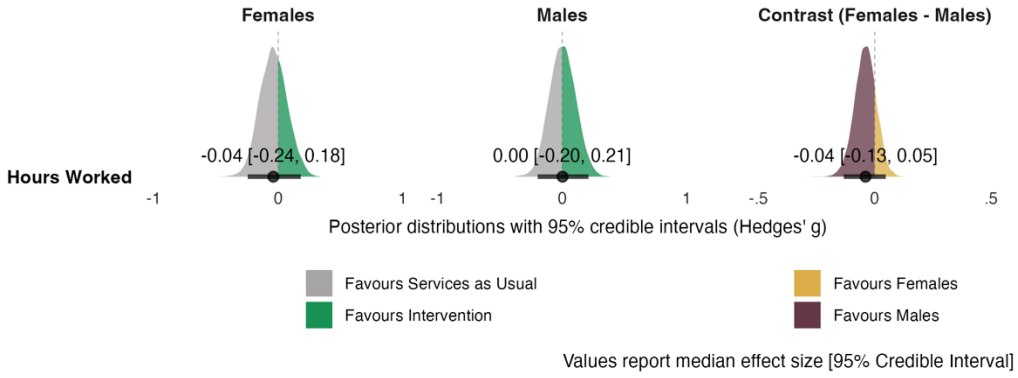
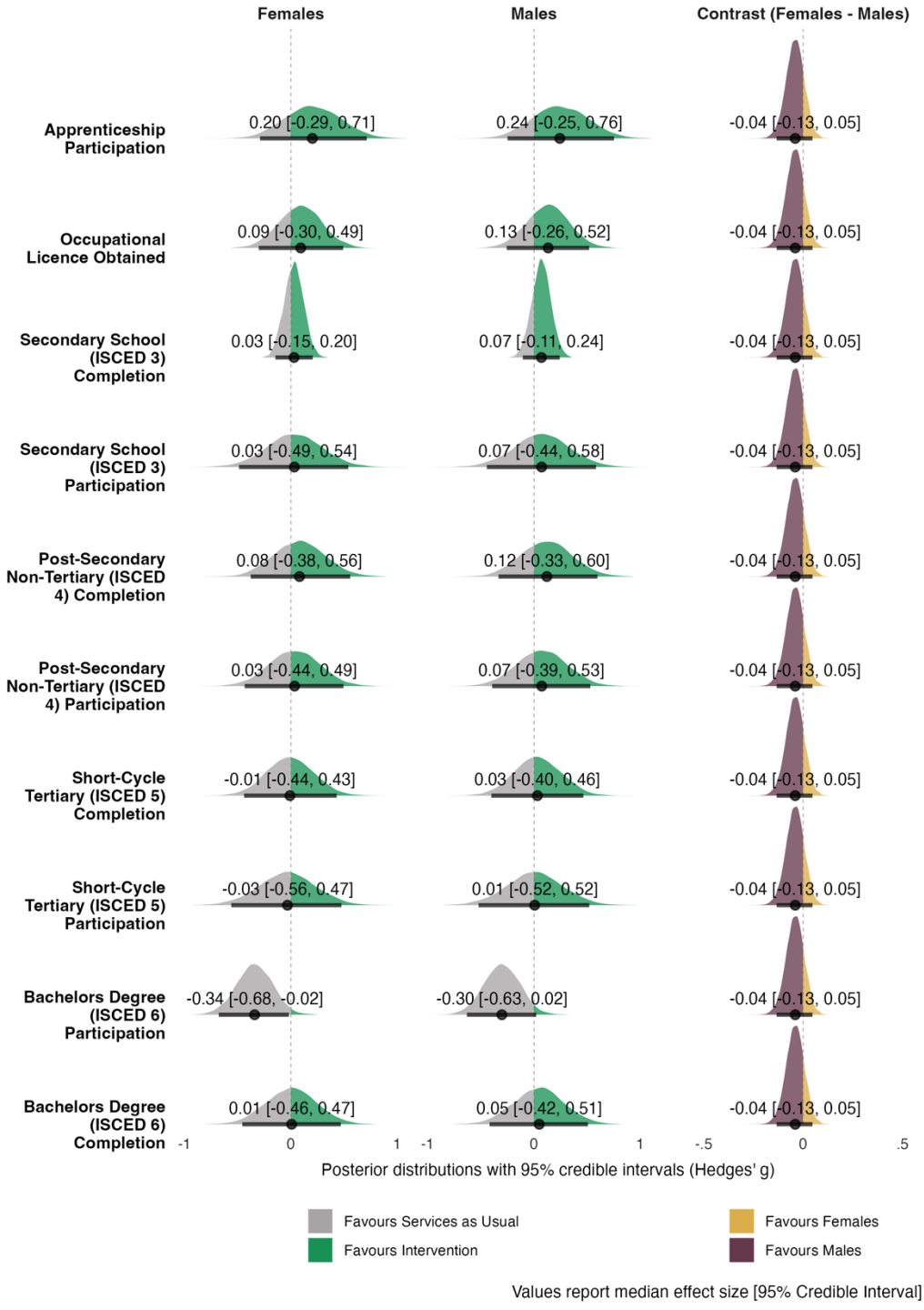


Figure 121 Impact of Soft Skills Training on Education and Skills



Behavioural Skills Training

Figure 122 Impact of Behavioural Skills Training on Labour Force status

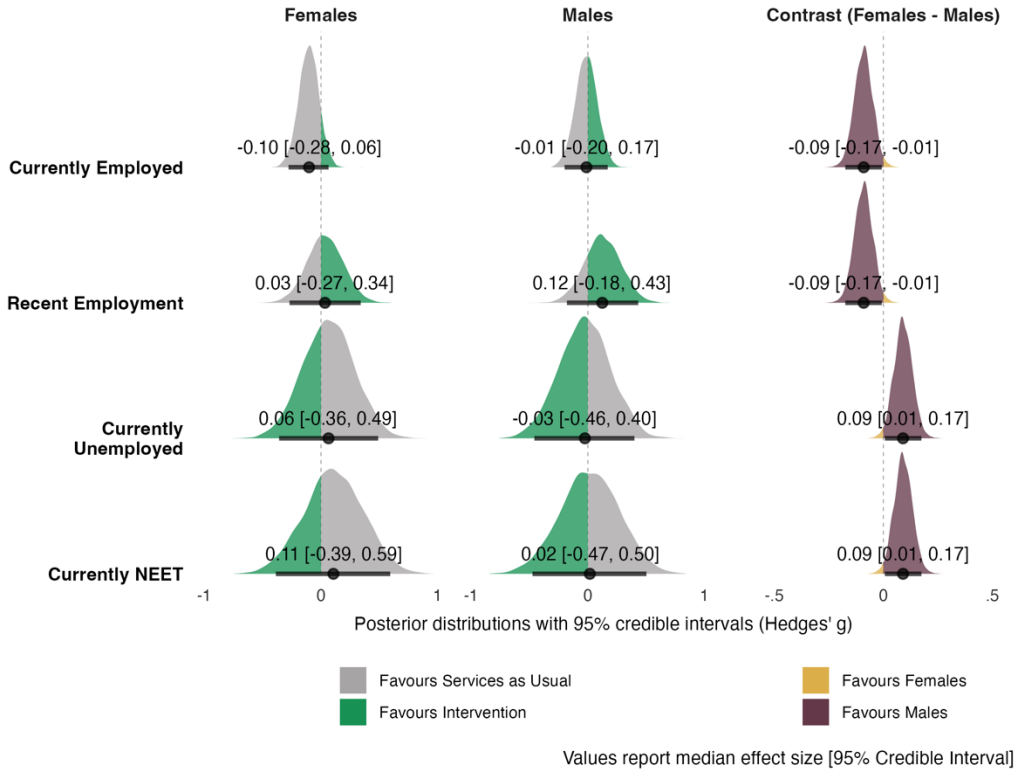


Figure 123 Impact of Behavioural Skills Training on Employment compensation

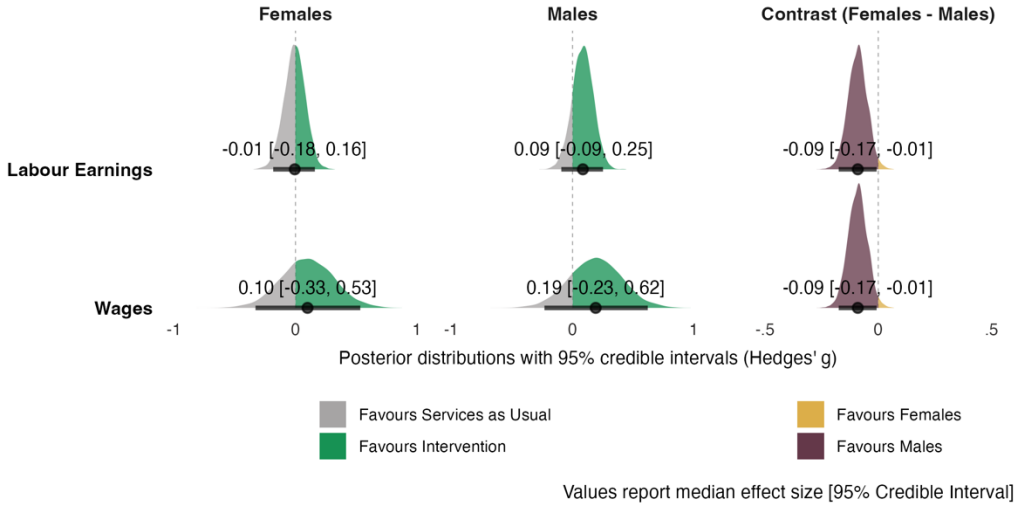


Figure 124 Impact of Behavioural Skills Training on Employment duration

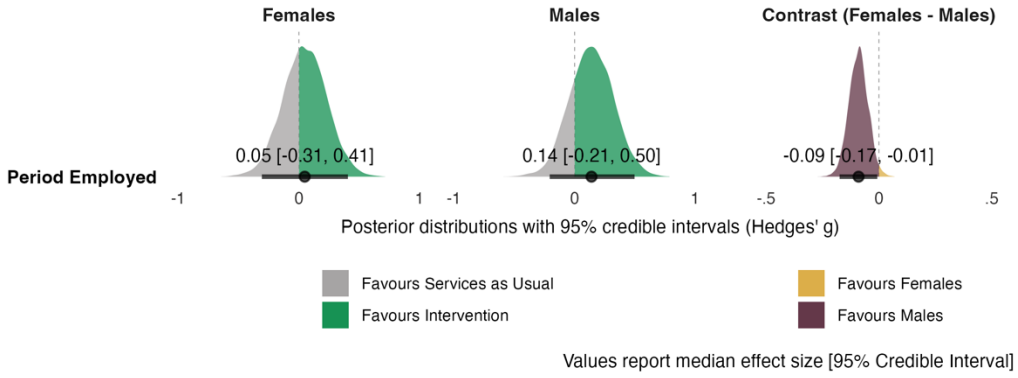


Figure 125 Impact of Behavioural Skills Training on Hours worked

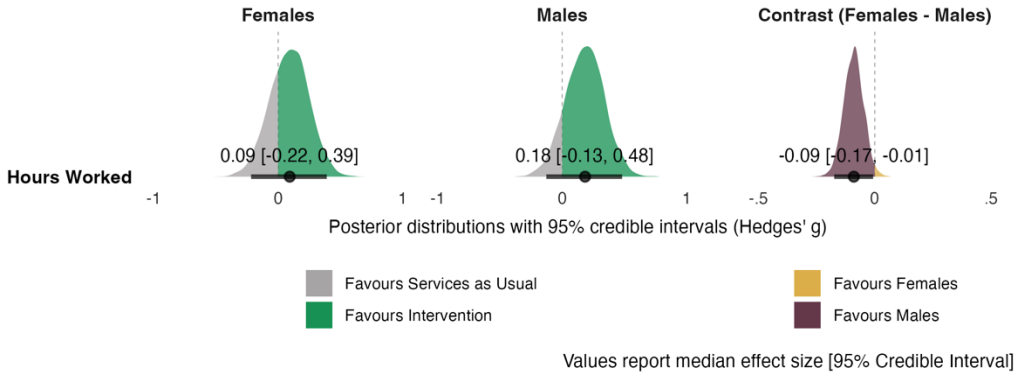
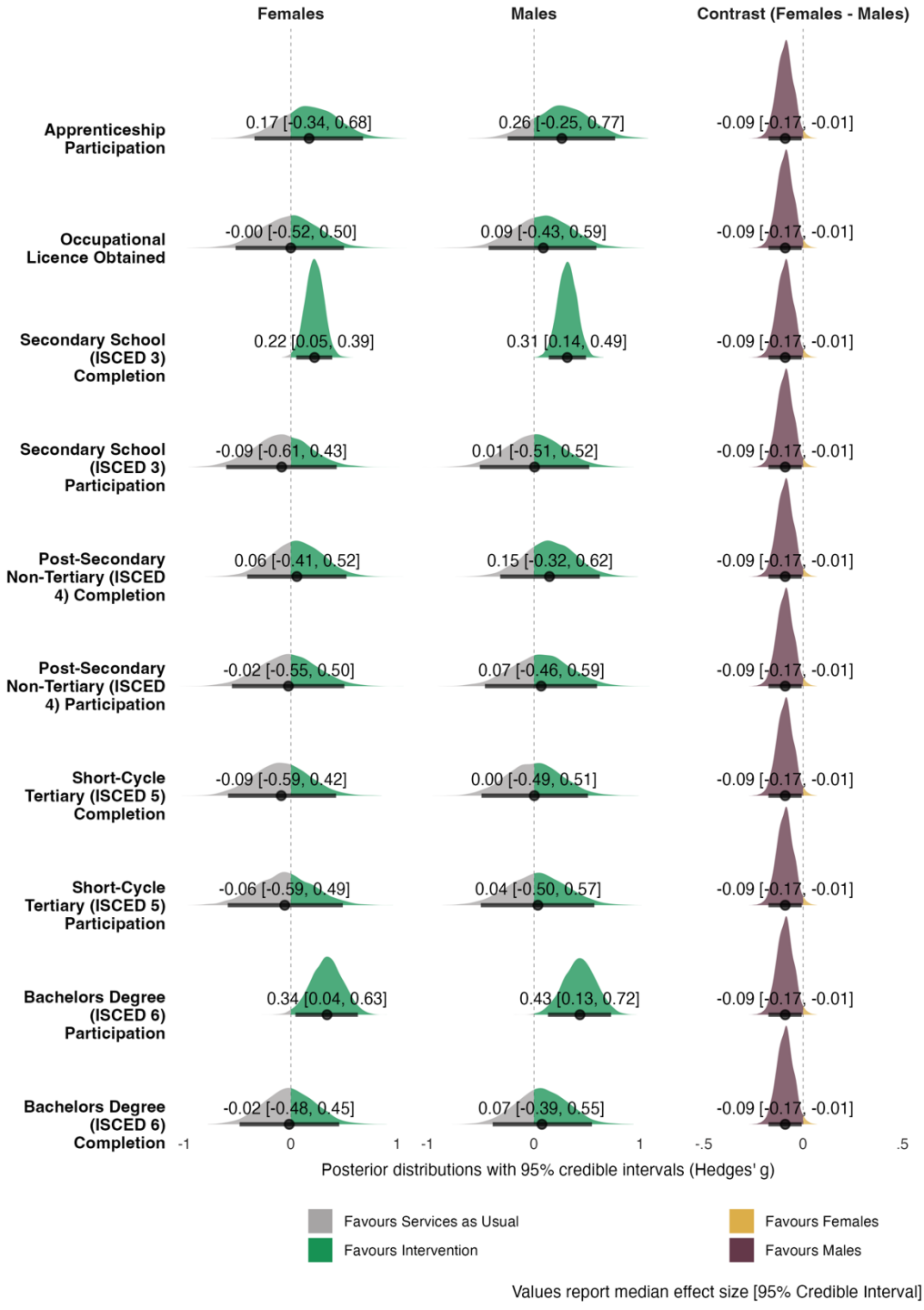


Figure 126 Impact of Behavioural Skills Training on Education and Skills



Job Specific Technical Skills (Off-Job Training)

Figure 127 Impact of Job Specific Technical Skills (Off-Job Training) on Labour Force status

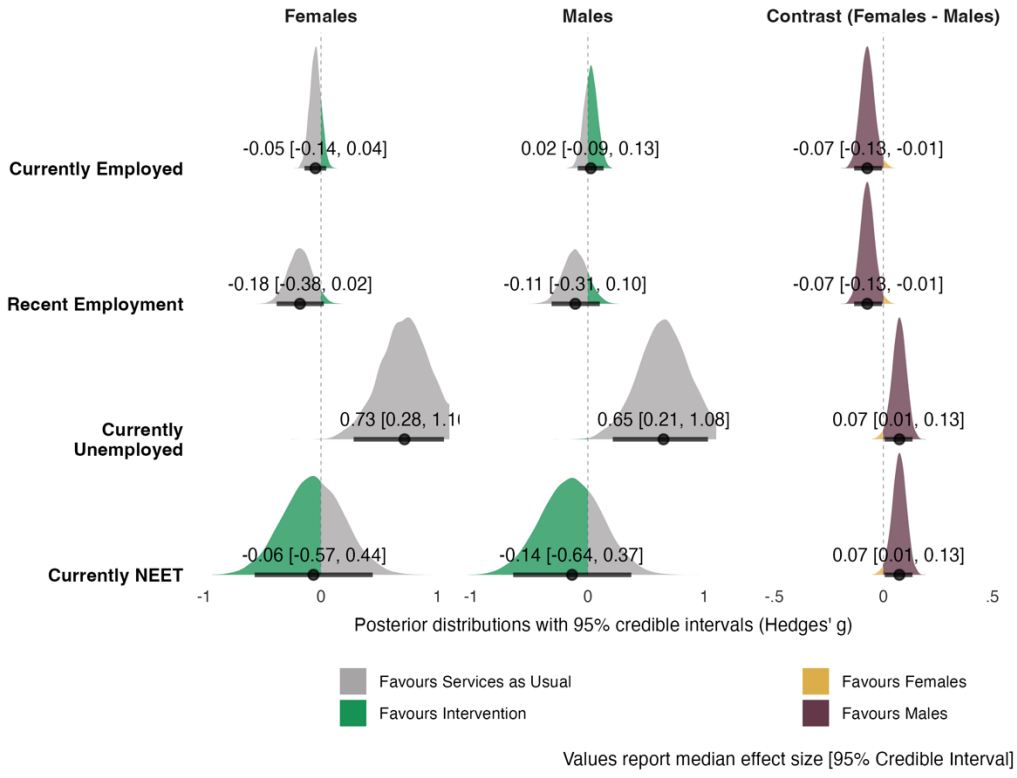


Figure 128 Impact of Job Specific Technical Skills (Off-Job Training) on Employment compensation

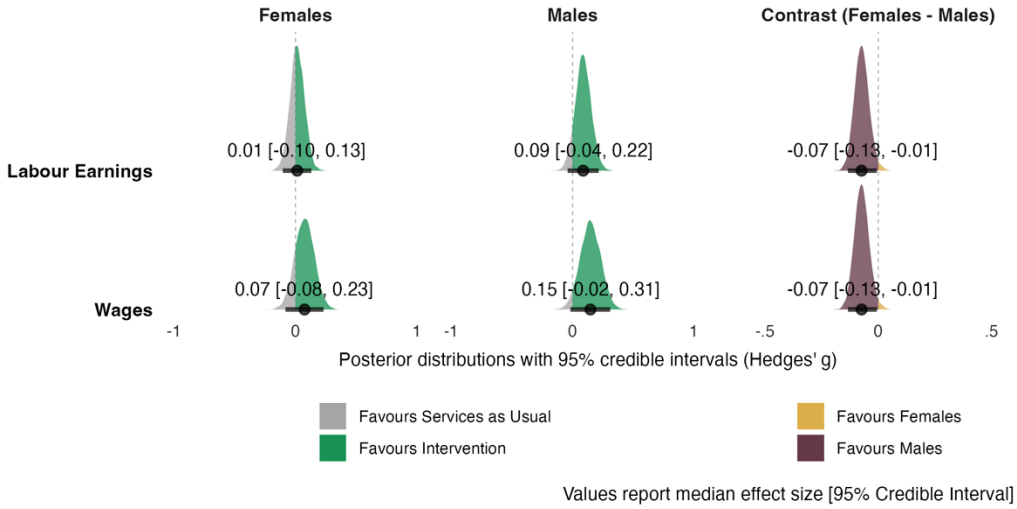


Figure 129 Impact of Job Specific Technical Skills (Off-Job Training) on Employment duration



Figure 130 Impact of Job Specific Technical Skills (Off-Job Training) on Hours worked

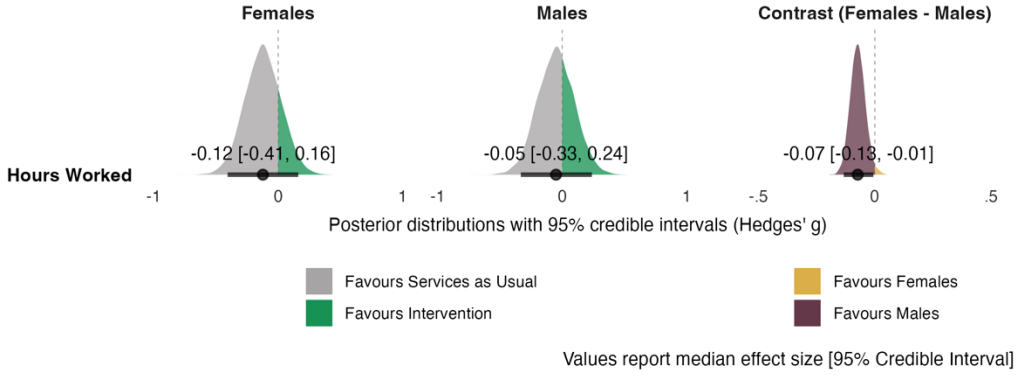
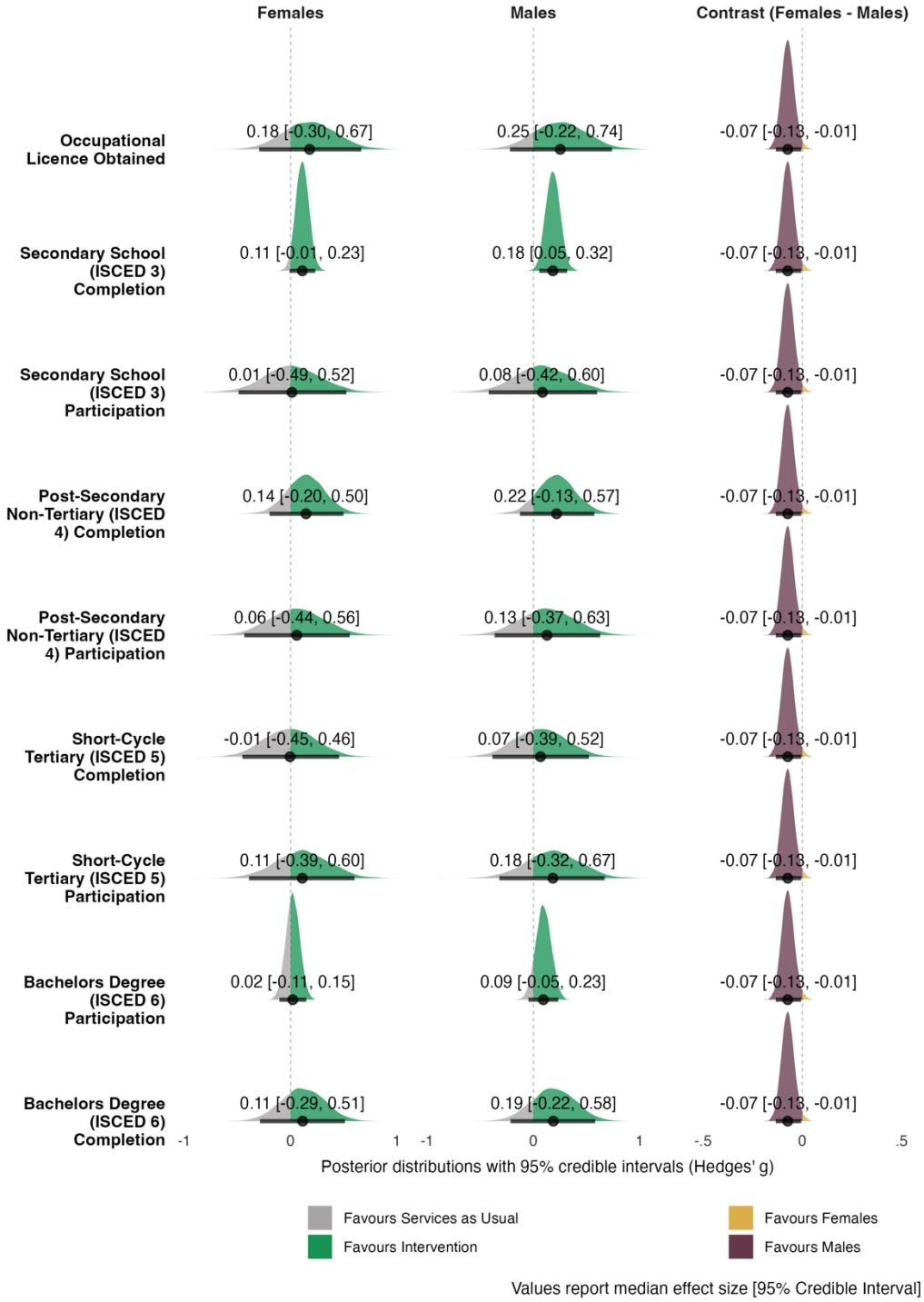


Figure 131 Impact of Job Specific Technical Skills (Off-Job Training) on Education and Skills



Self-Employment Support

Figure 132 Impact of Self-Employment Support on Labour Force status

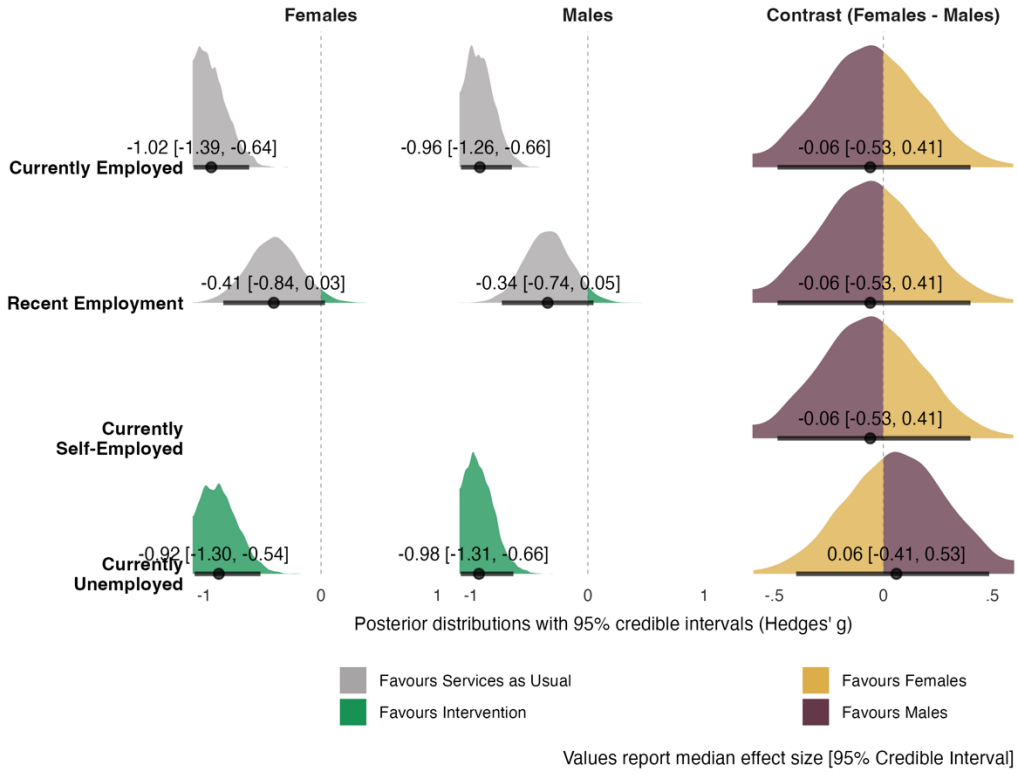


Figure 133 Impact of Self-Employment Support on Employment duration

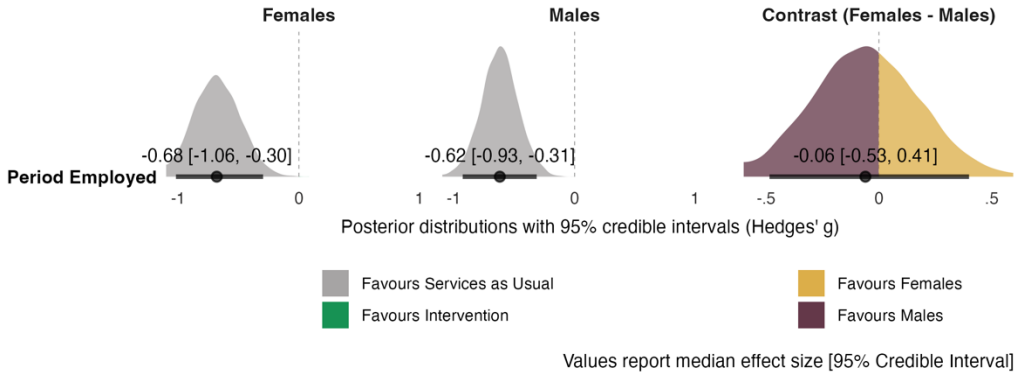
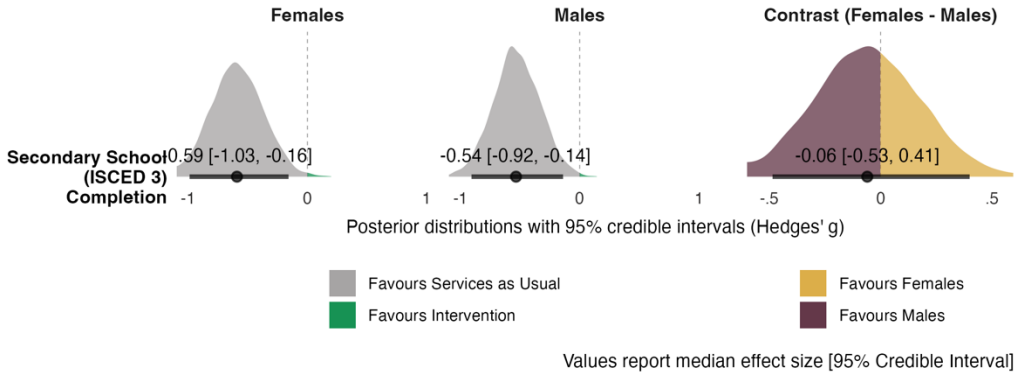


Figure 134 Impact of Self-Employment Support on Education and Skills



Job Search Preparation

Figure 135 Impact of Job Search Preparation on Labour Force status

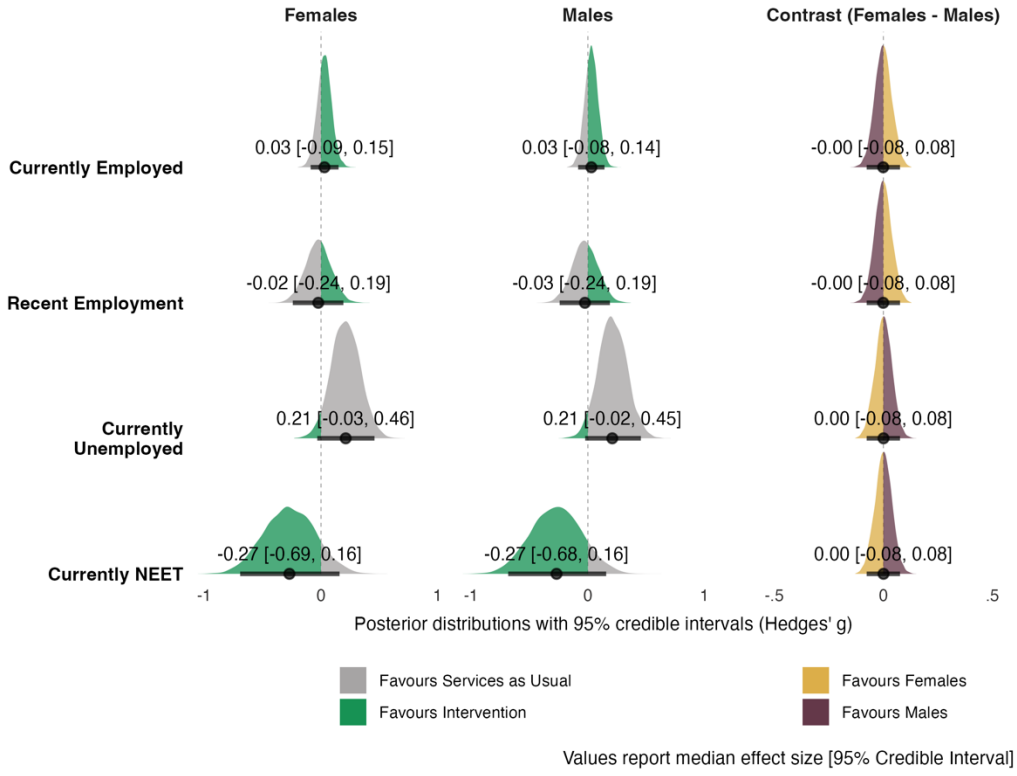


Figure 136 Impact of Job Search Preparation on Employment compensation

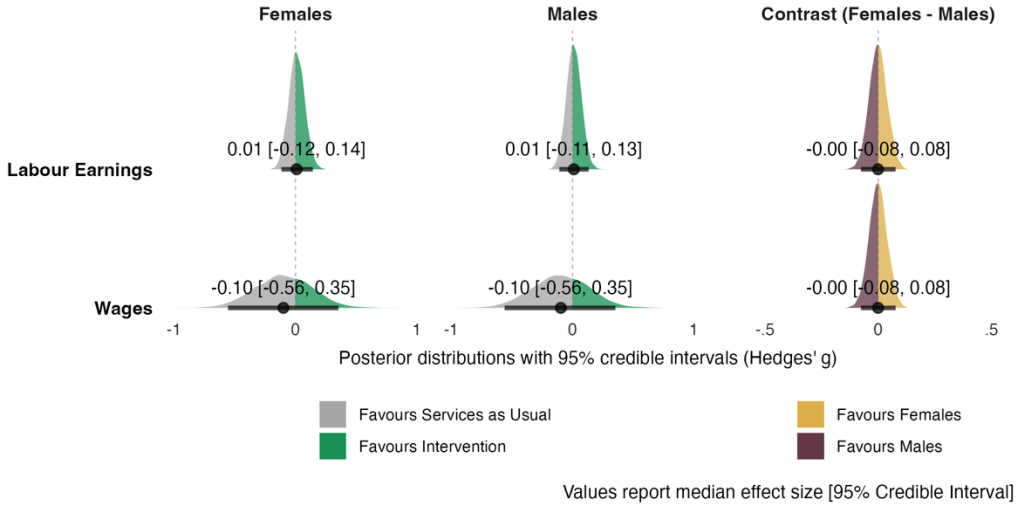


Figure 137 Impact of Job Search Preparation on Employment duration

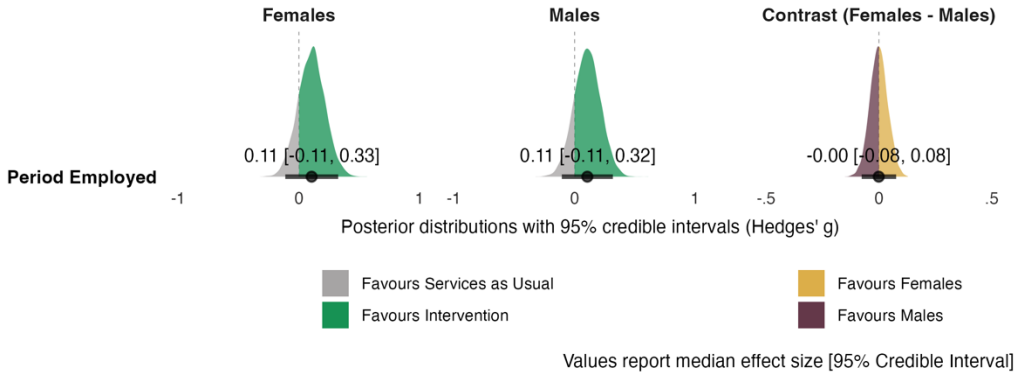


Figure 138 Impact of Job Search Preparation on Hours worked

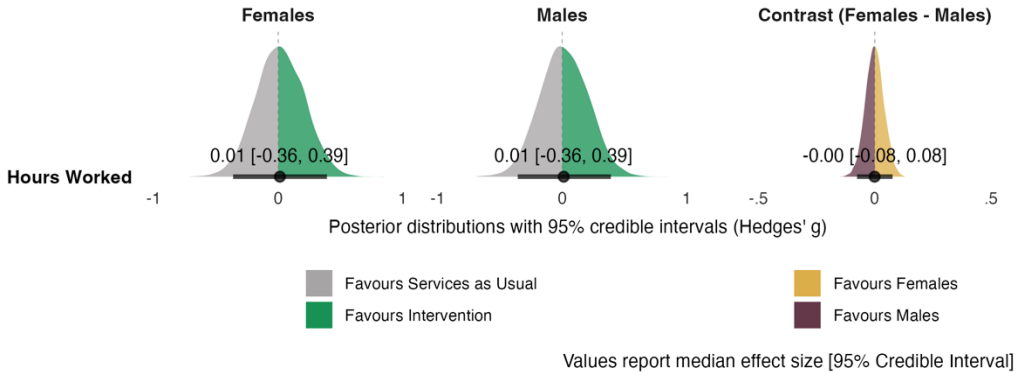


Figure 139 Impact of Job Search Preparation on Education and Skills



Job Search Assistance

Figure 140 Impact of Job Search Assistance on Labour Force status

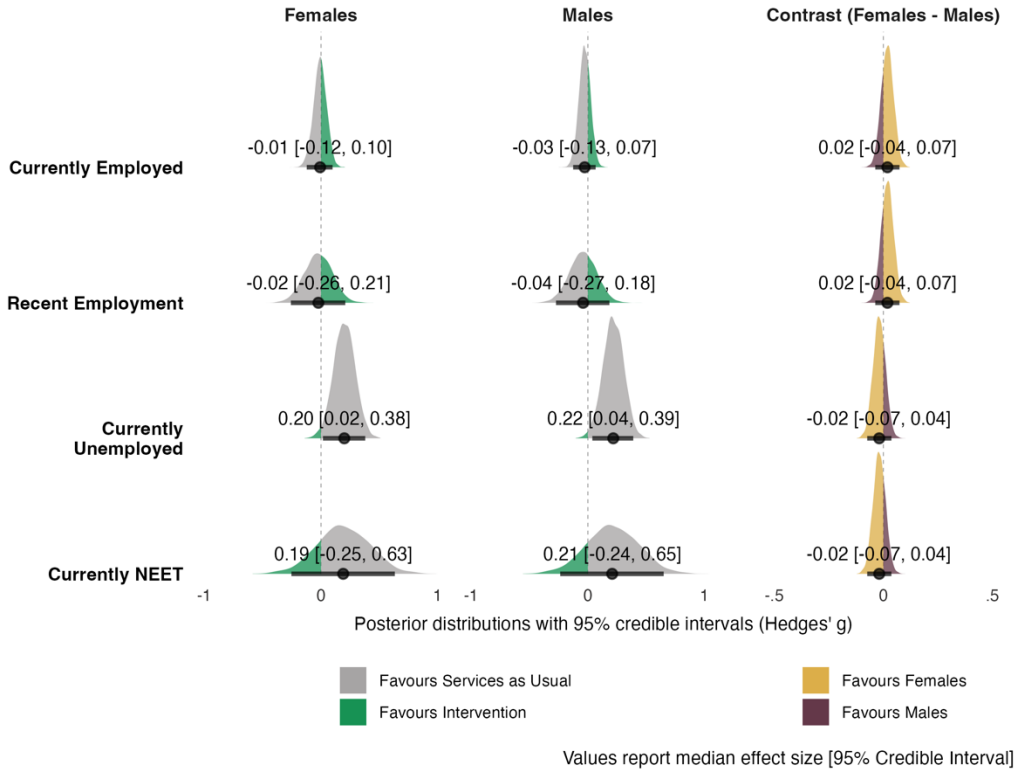


Figure 141 Impact of Job Search Assistance on Employment compensation

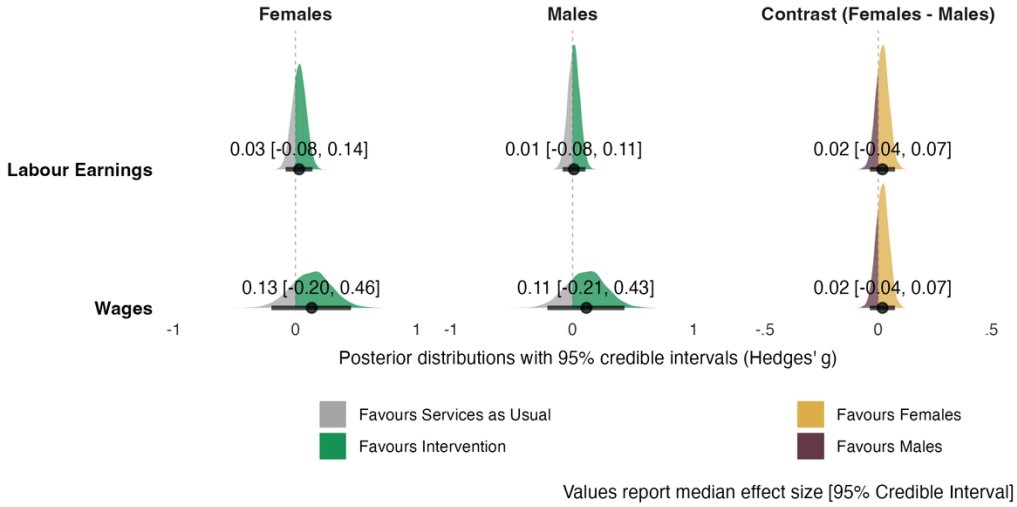


Figure 142 Impact of Job Search Assistance on Employment duration



Figure 143 Impact of Job Search Assistance on Hours worked

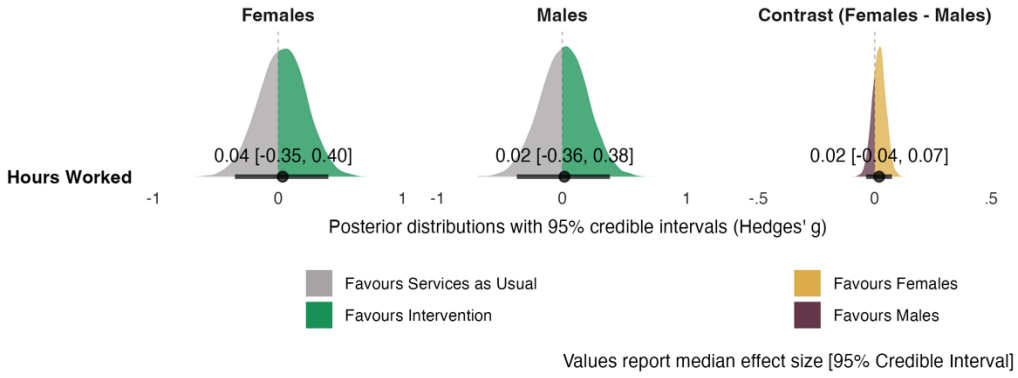


Figure 144 Impact of Job Search Assistance on Education and Skills



Employment Counselling

Figure 145 Impact of Employment Counselling on Labour Force status

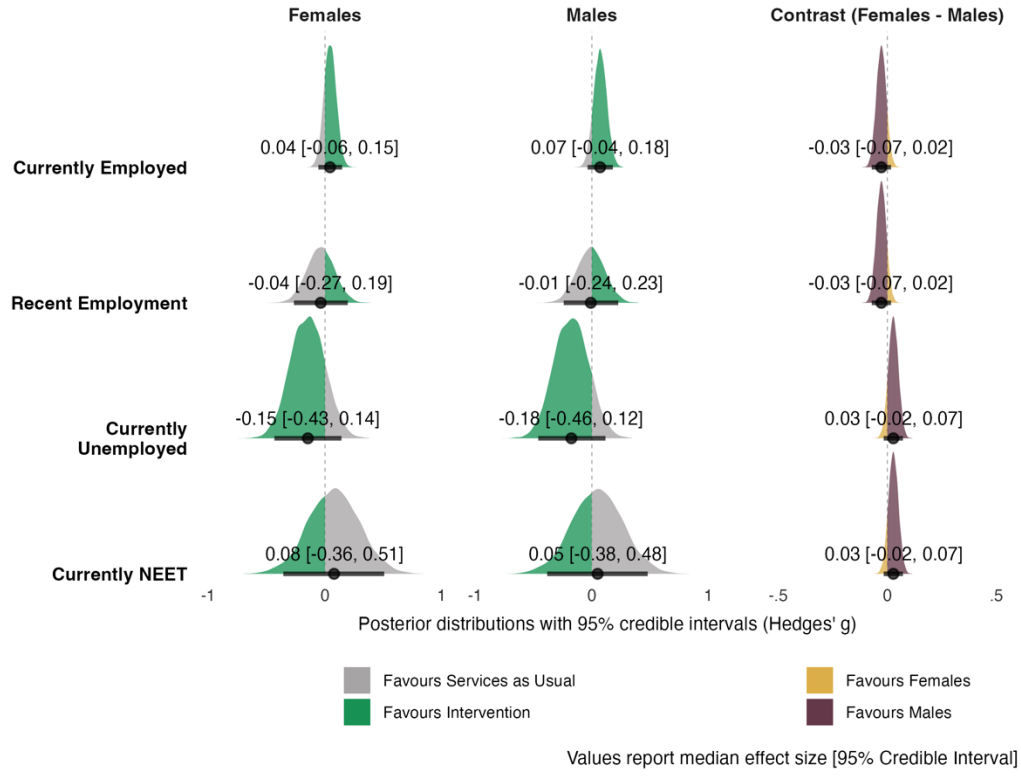


Figure 146 Impact of Employment Counselling on Employment compensation

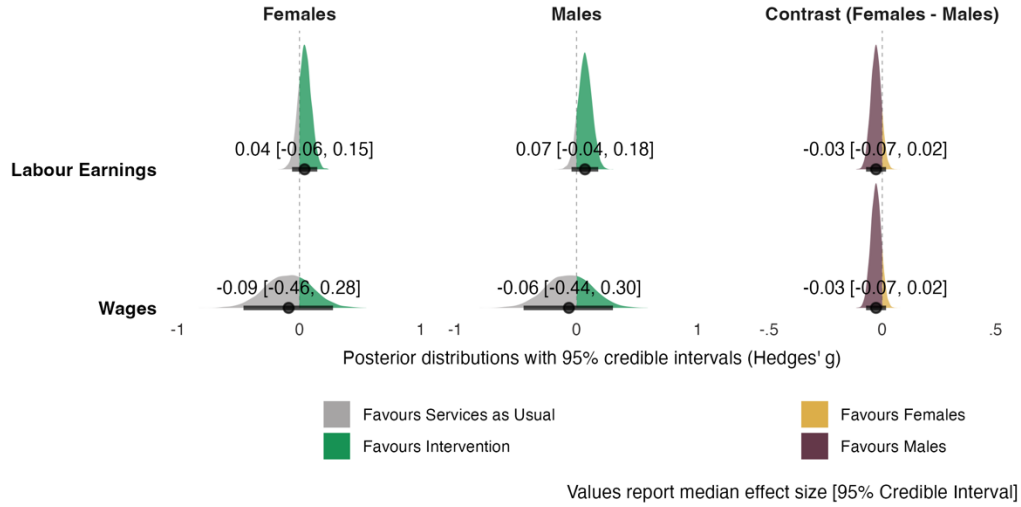


Figure 147 Impact of Employment Counselling on Employment duration

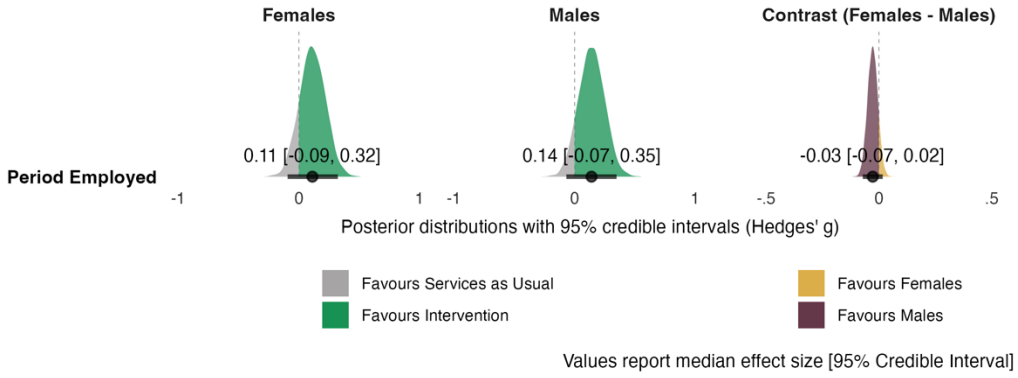


Figure 148 Impact of Employment Counselling on Hours worked

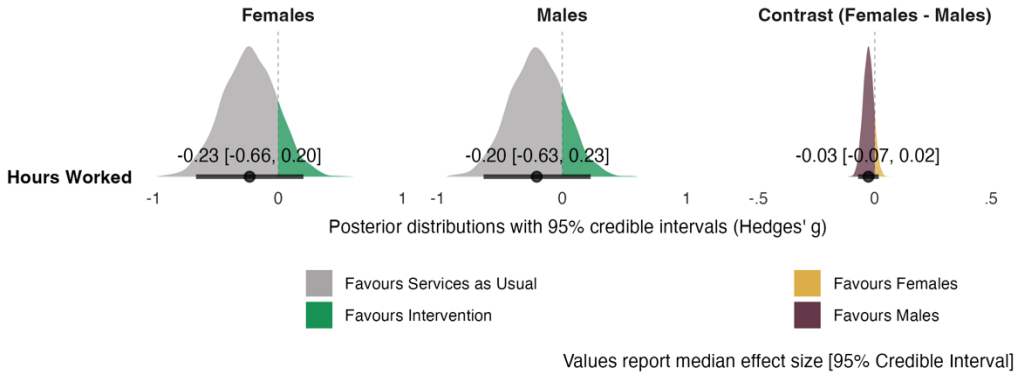


Figure 149 Impact of Employment Counselling on Education and Skills



Employment Coaching

Figure 150 Impact of Employment Coaching on Labour Force status

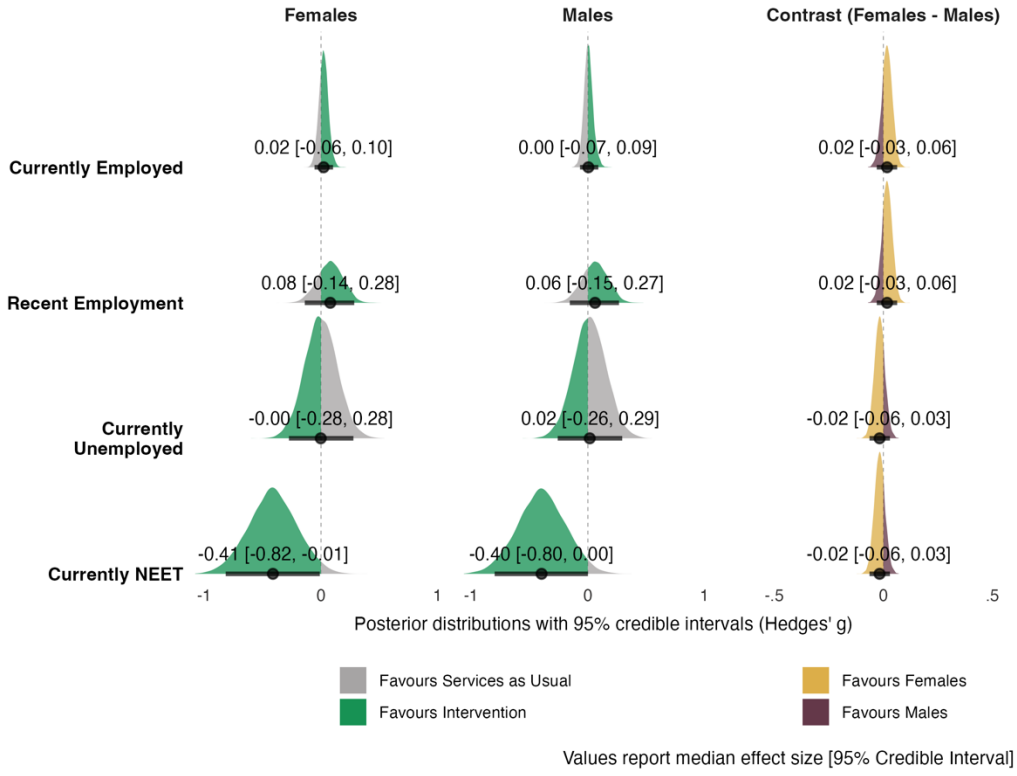


Figure 151 Impact of Employment Coaching on Employment compensation

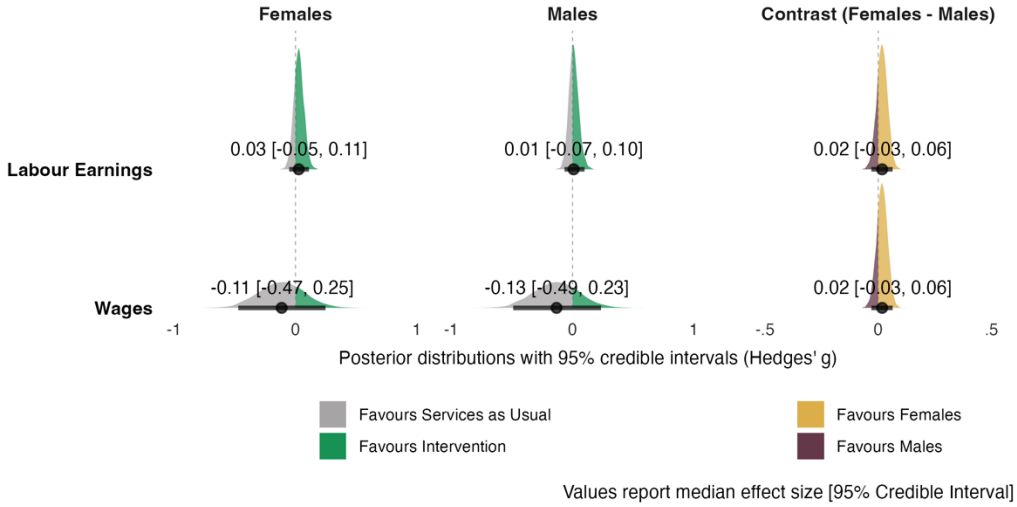


Figure 152 Impact of Employment Coaching on Employment duration

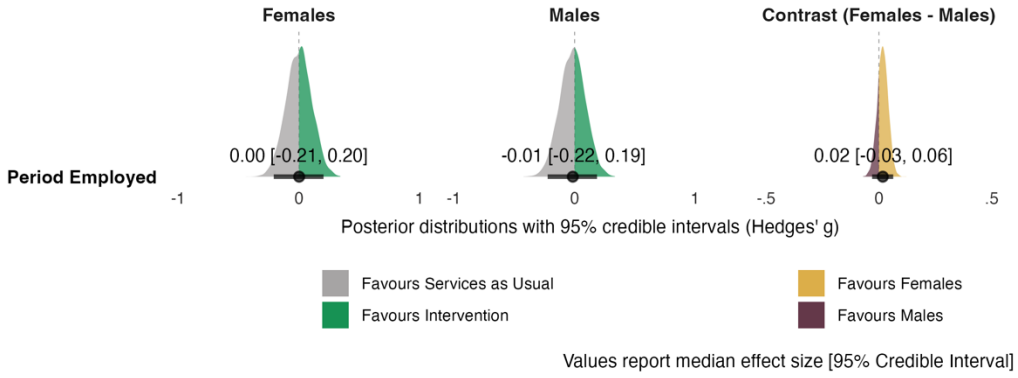


Figure 153 Impact of Employment Coaching on Hours worked

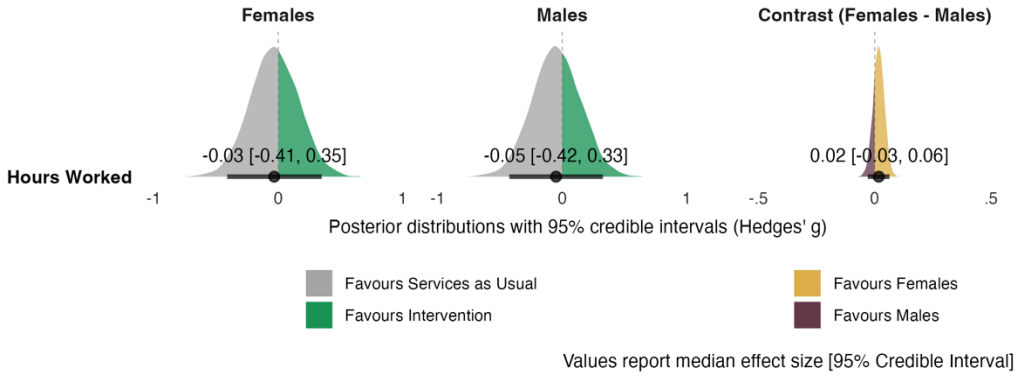
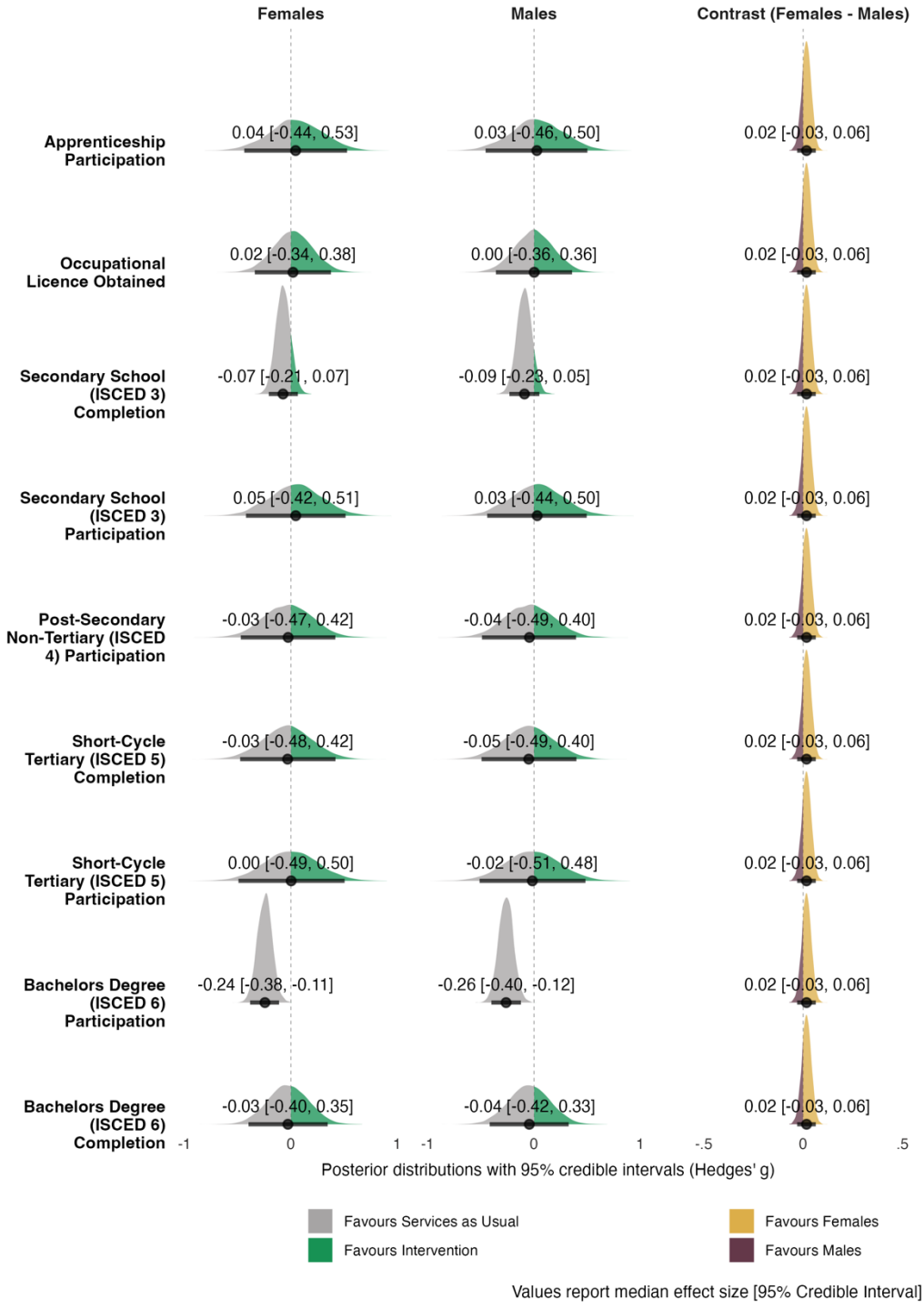


Figure 154 Impact of Employment Coaching on Education and Skills



Financial Assistance

Figure 155 Impact of Financial Assistance on Labour Force status

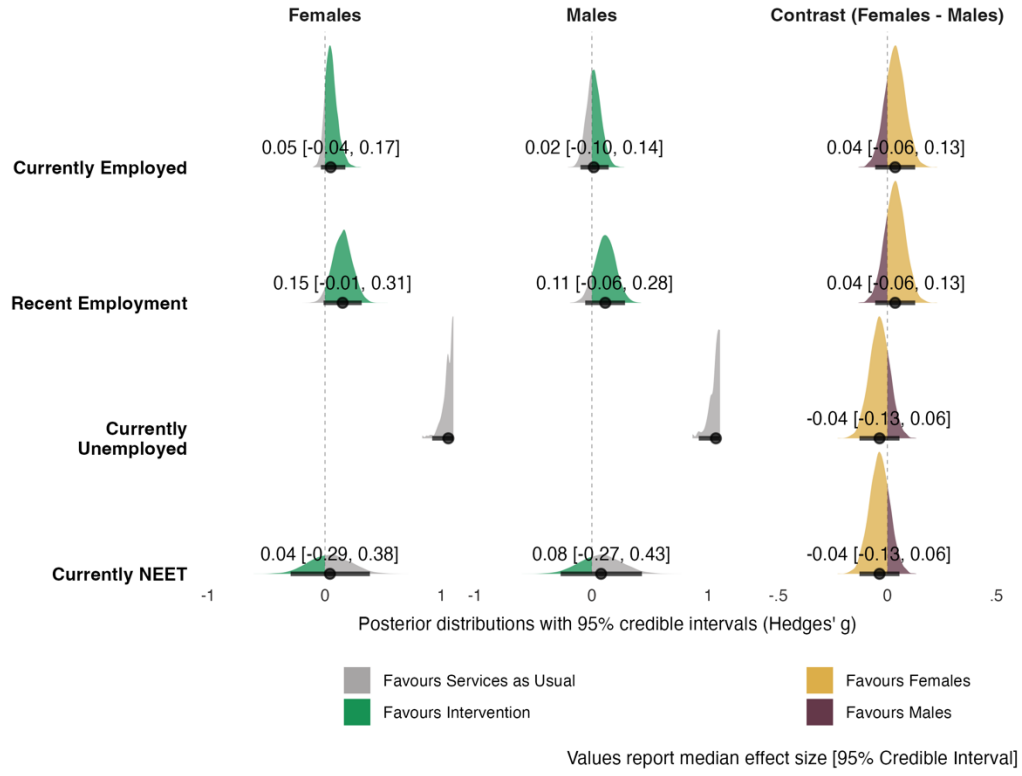


Figure 156 Impact of Financial Assistance on Employment compensation

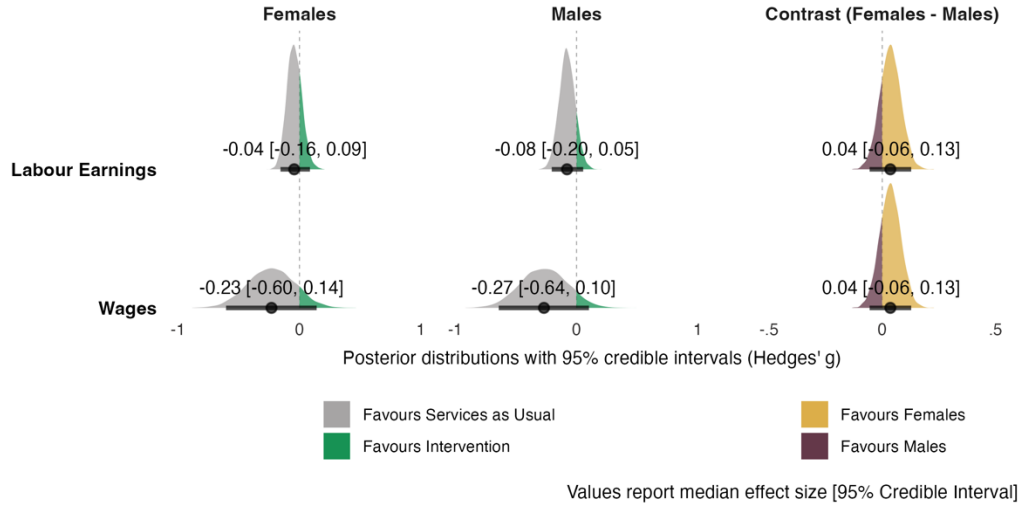


Figure 157 Impact of Financial Assistance on Employment duration

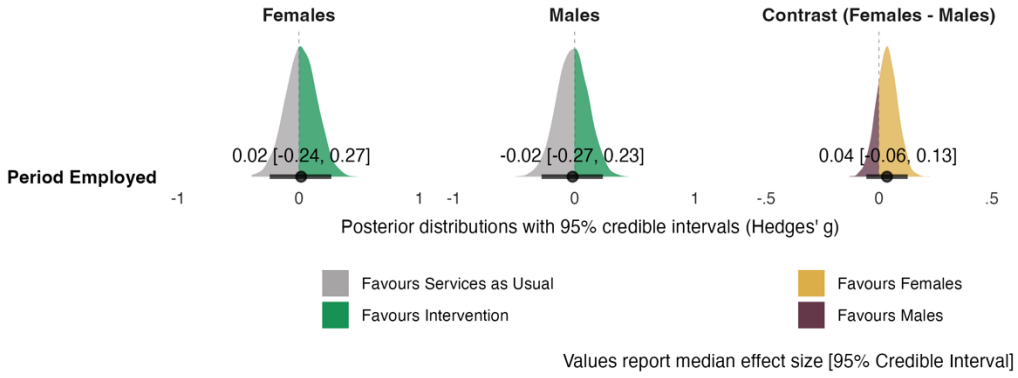


Figure 158 Impact of Financial Assistance on Hours worked

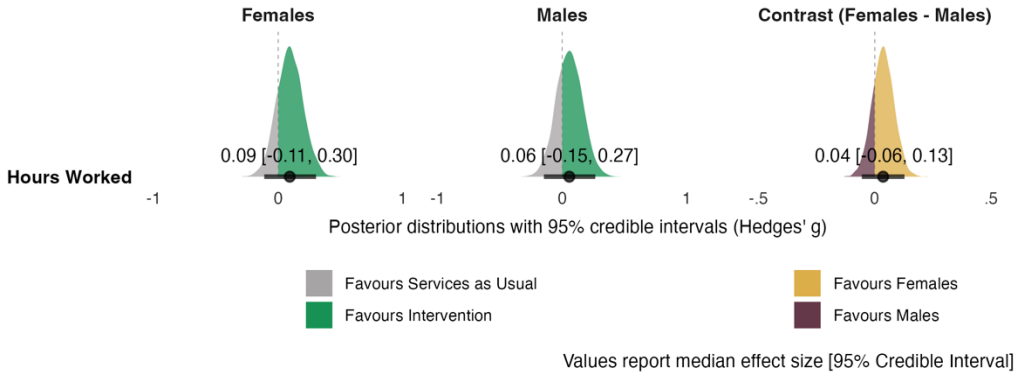


Figure 159 Impact of Financial Assistance on Education and Skills



Job Specific Technical Skills (On-Job Training)

Figure 160 Impact of Job Specific Technical Skills (On-Job Training) on Labour Force status

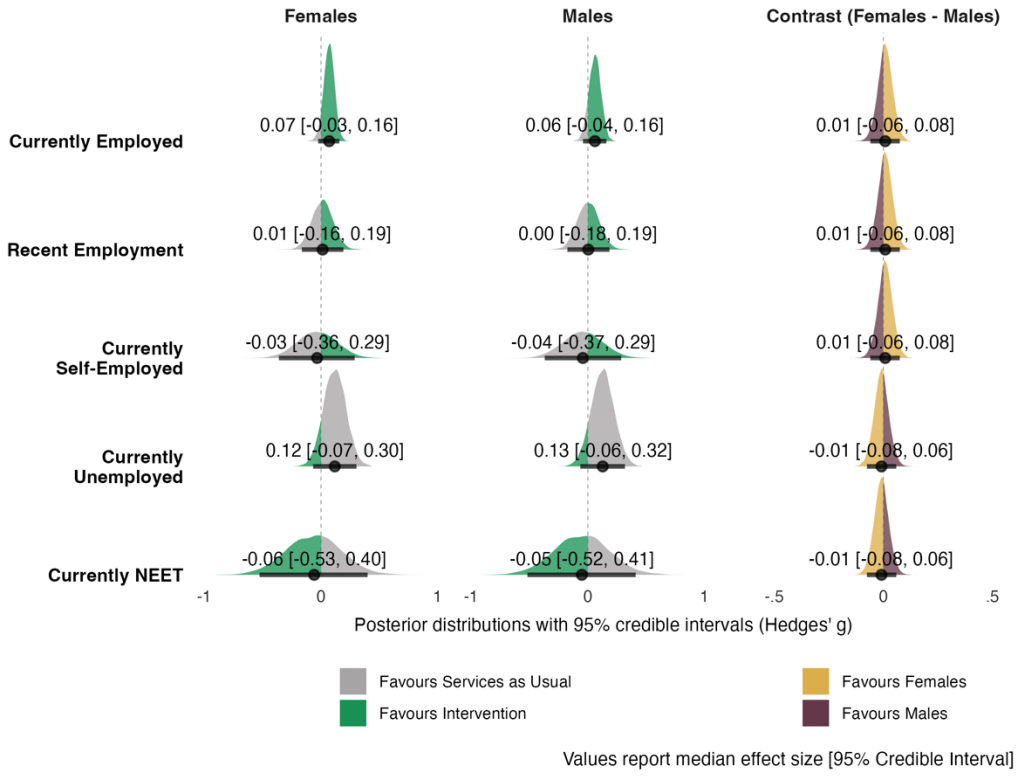


Figure 161 Impact of Job Specific Technical Skills (On-Job Training) on Employment compensation

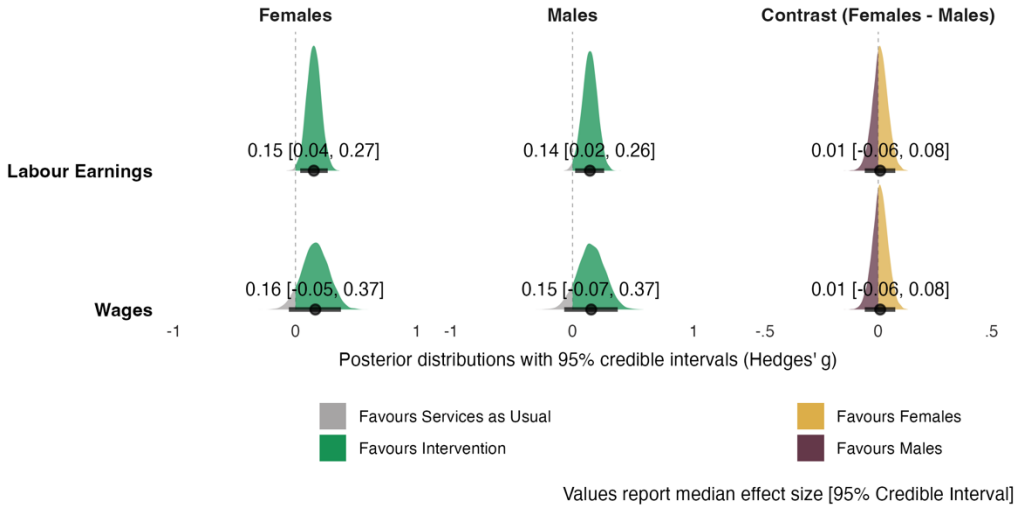


Figure 162 Impact of Job Specific Technical Skills (On-Job Training) on Employment duration



Figure 163 Impact of Job Specific Technical Skills (On-Job Training) on Hours worked

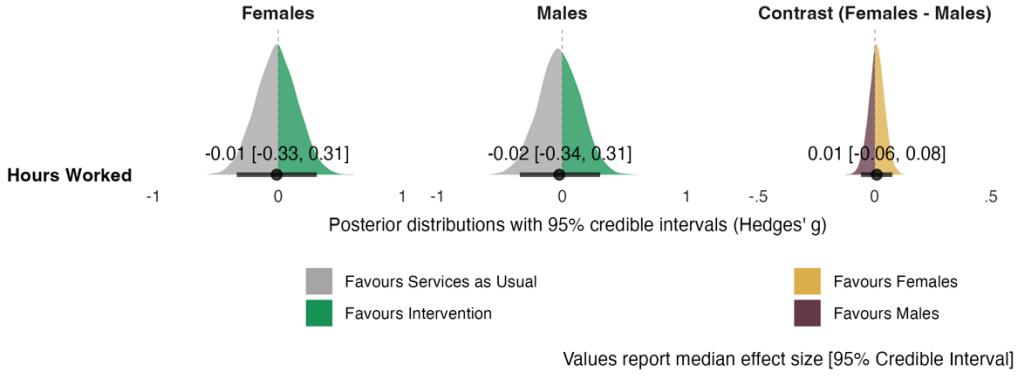


Figure 164 Impact of Job Specific Technical Skills (On-Job Training) on Education and Skills



Paid Temporary Work Experience

Figure 165 Impact of Paid Temporary Work Experience on Labour Force status

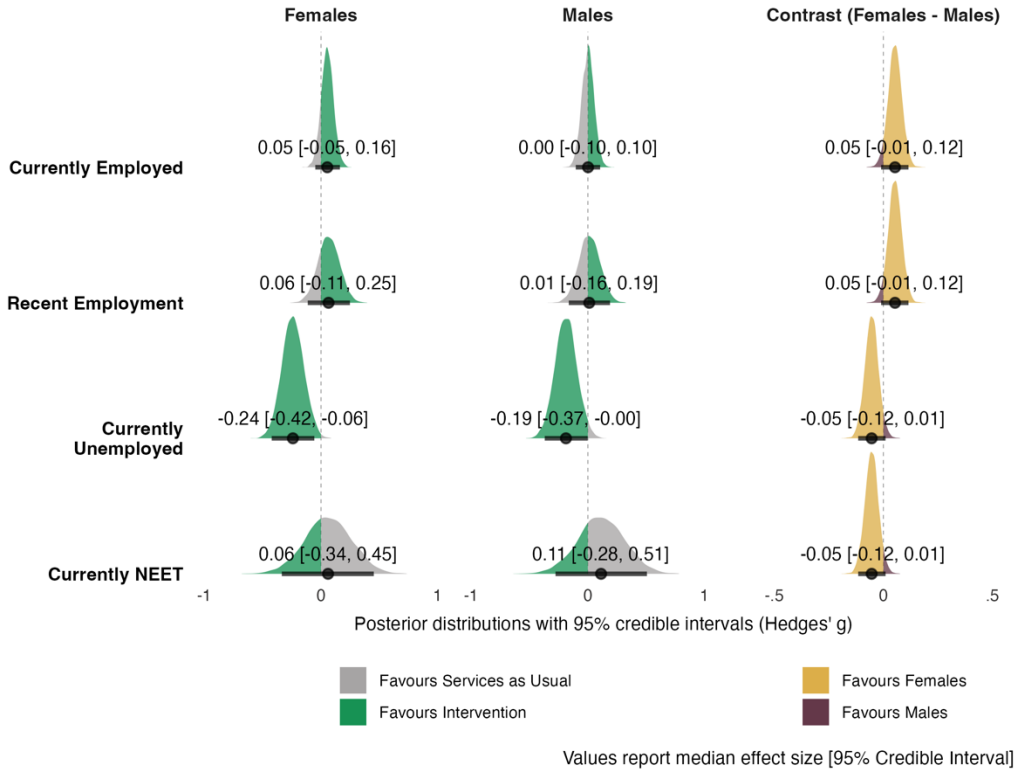


Figure 166 Impact of Paid Temporary Work Experience on Employment compensation

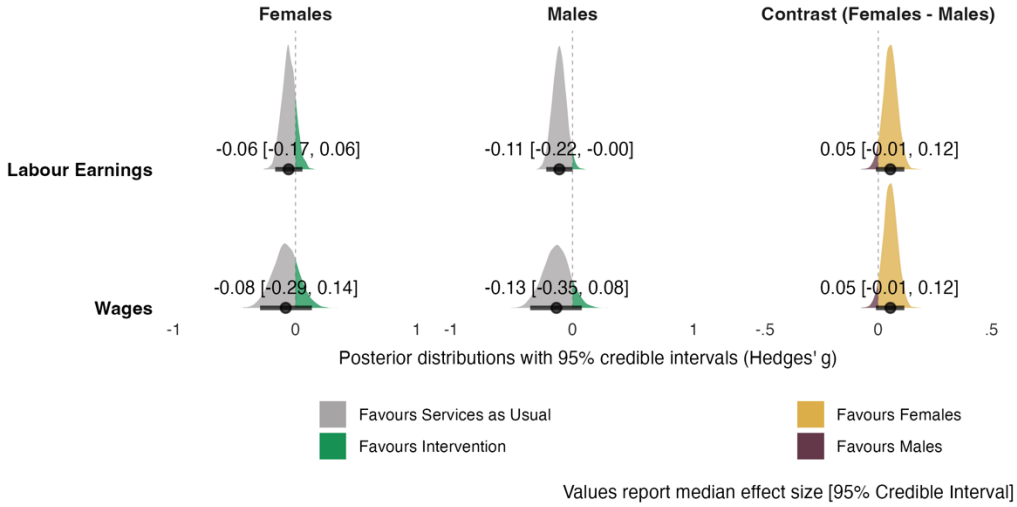


Figure 167 Impact of Paid Temporary Work Experience on Employment duration



Figure 168 Impact of Paid Temporary Work Experience on Hours worked

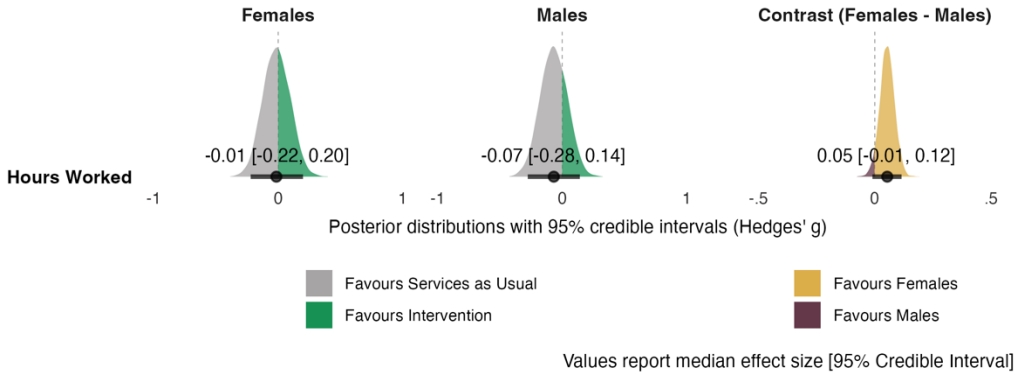


Figure 169 Impact of Paid Temporary Work Experience on Education and Skills



Unpaid Temporary Work Experience

Figure 170 Impact of Unpaid Temporary Work Experience on Labour Force status

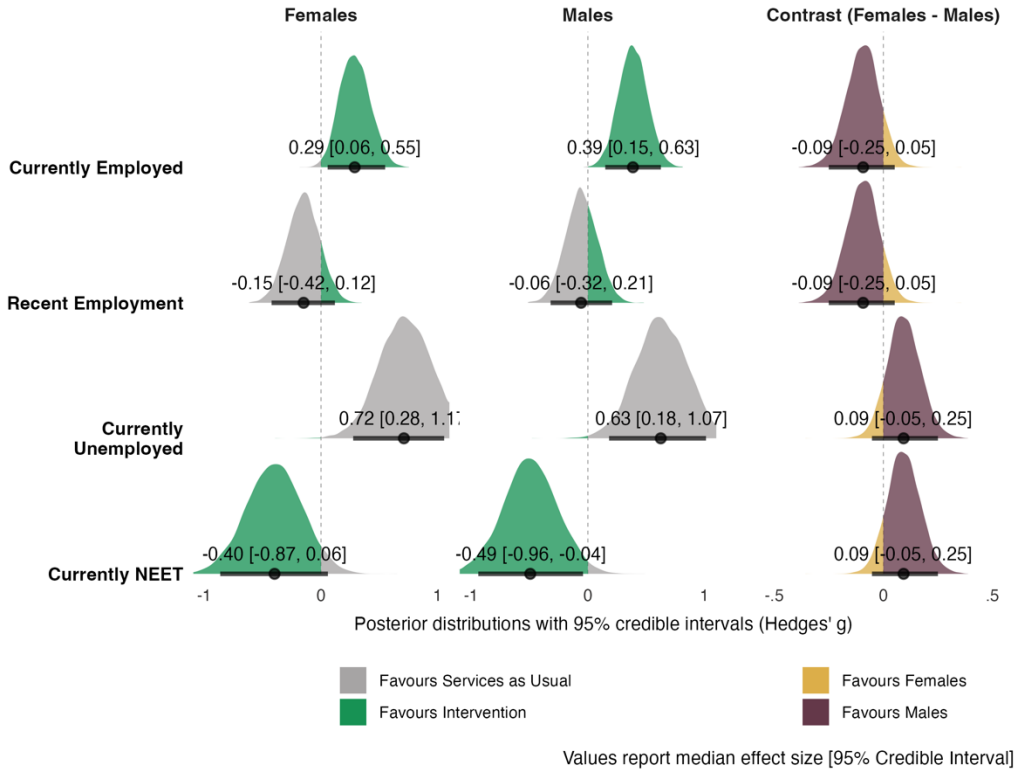


Figure 171 Impact of Unpaid Temporary Work Experience on Employment compensation

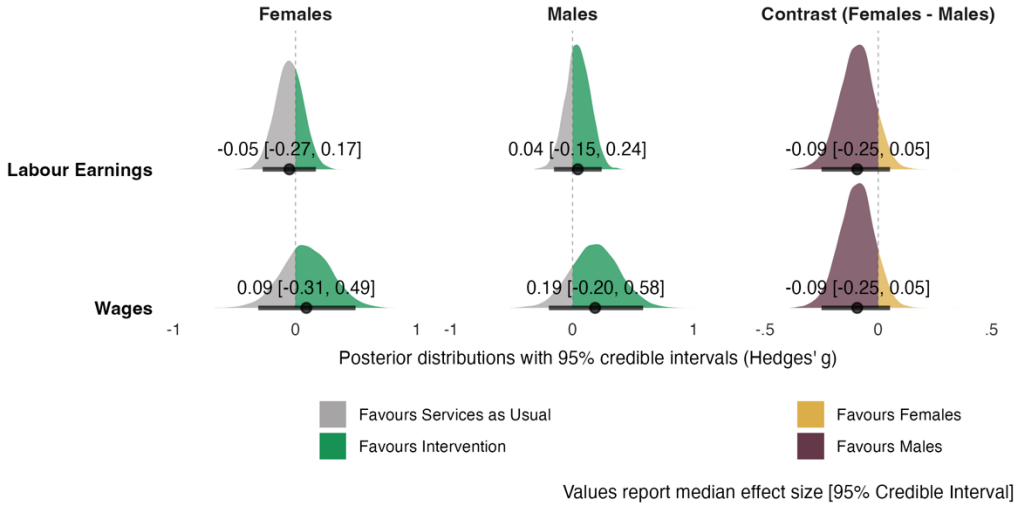


Figure 172 Impact of Unpaid Temporary Work Experience on Employment duration

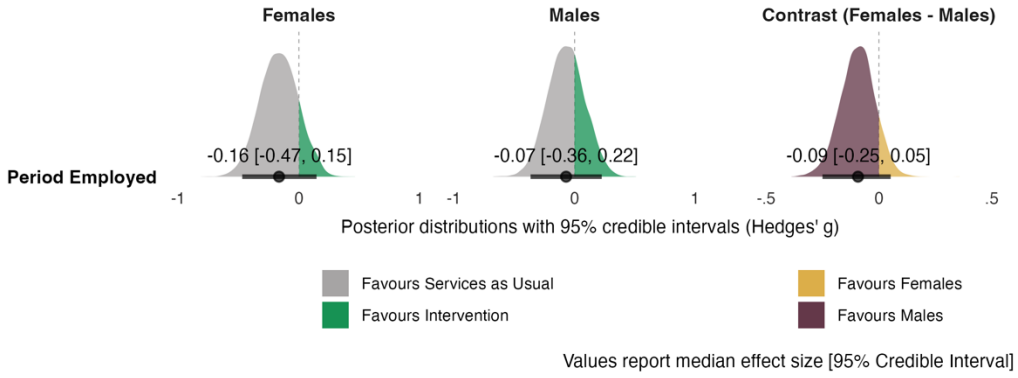


Figure 173 Impact of Unpaid Temporary Work Experience on Hours worked

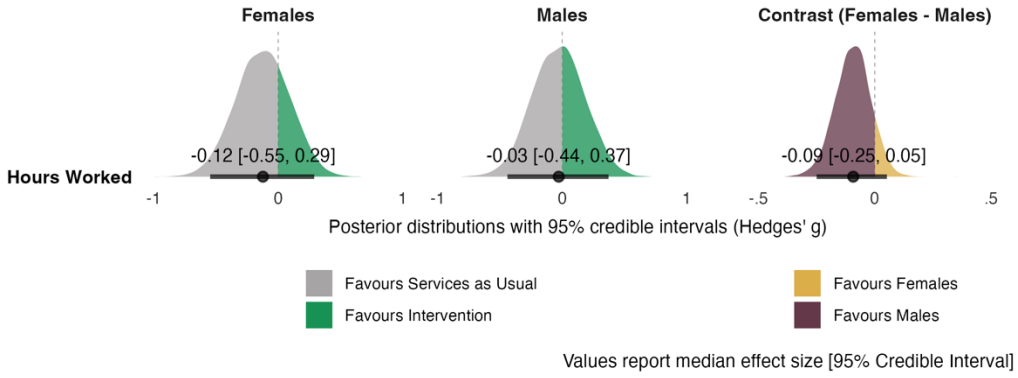
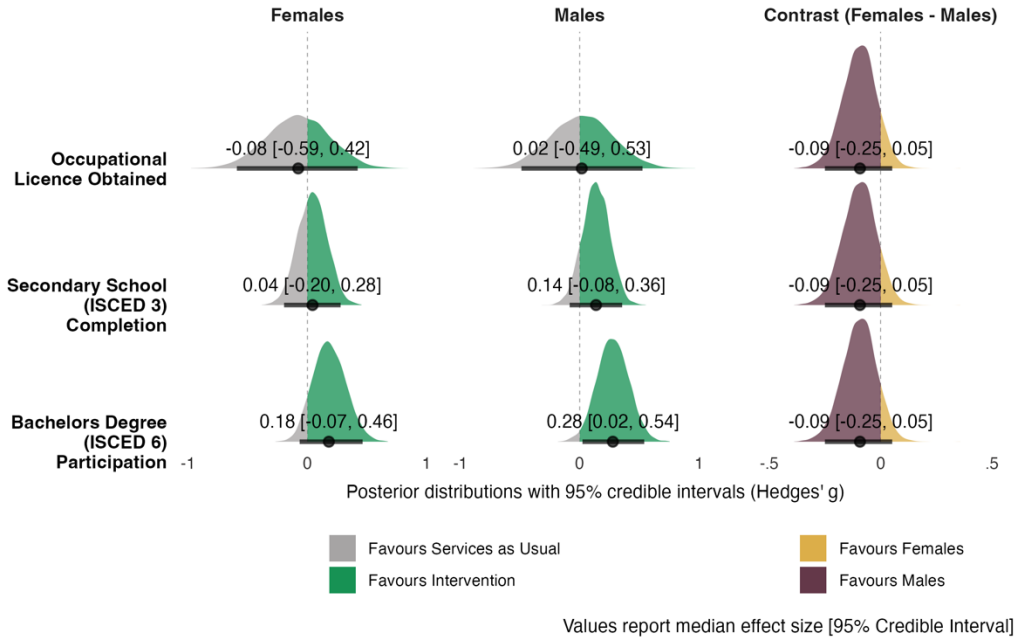


Figure 174 Impact of Unpaid Temporary Work Experience on Education and Skills



Wage Subsidies

Figure 175 Impact of Wage Subsidies on Labour Force status

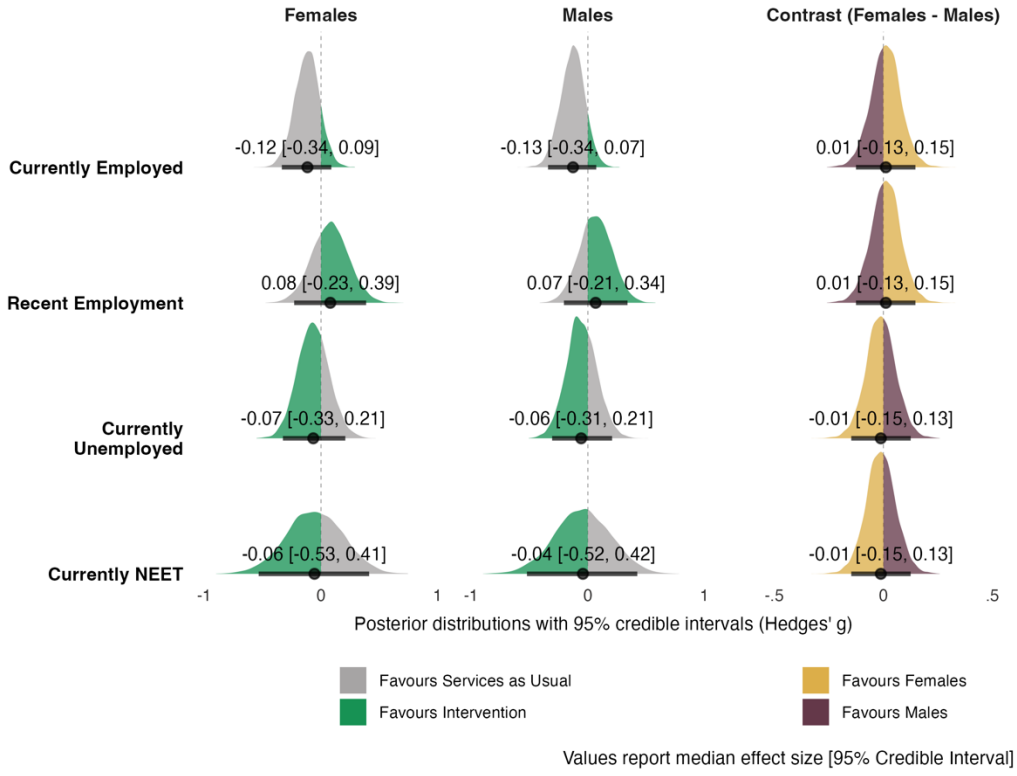


Figure 176 Impact of Wage Subsidies on Employment compensation

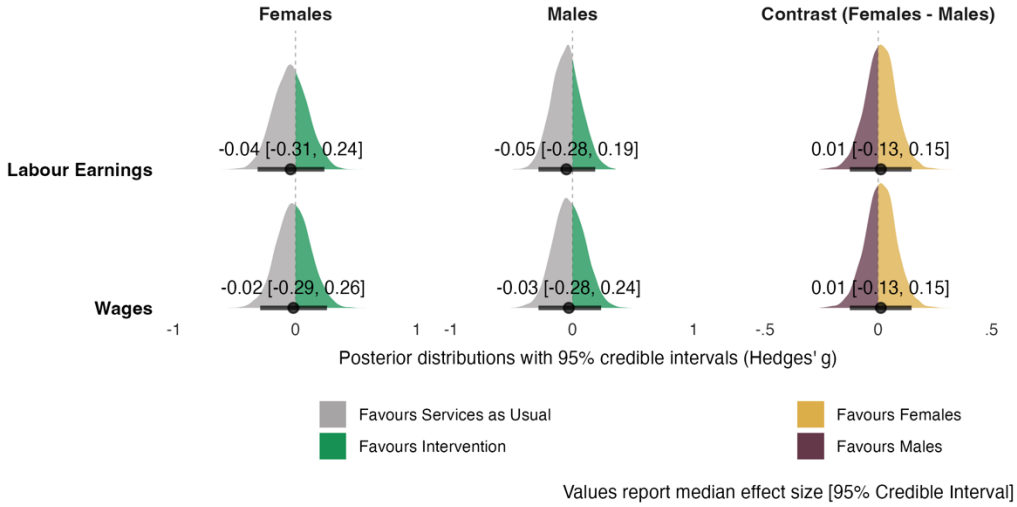


Figure 177 Impact of Wage Subsidies on Employment duration



Figure 178 Impact of Wage Subsidies on Hours worked

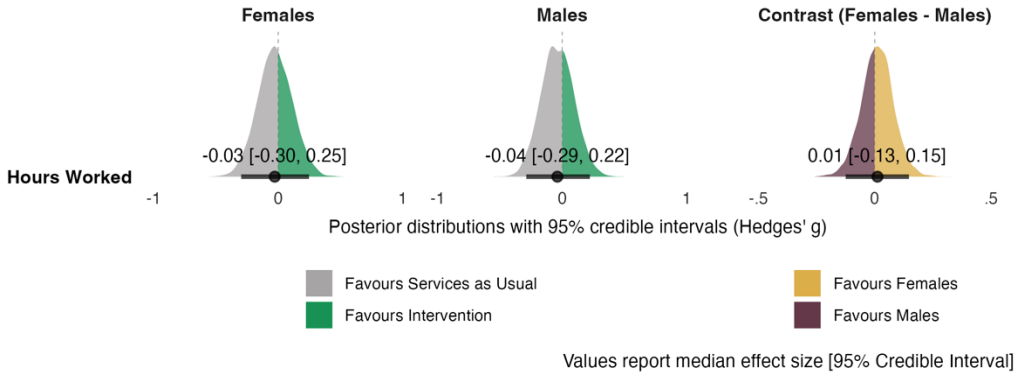
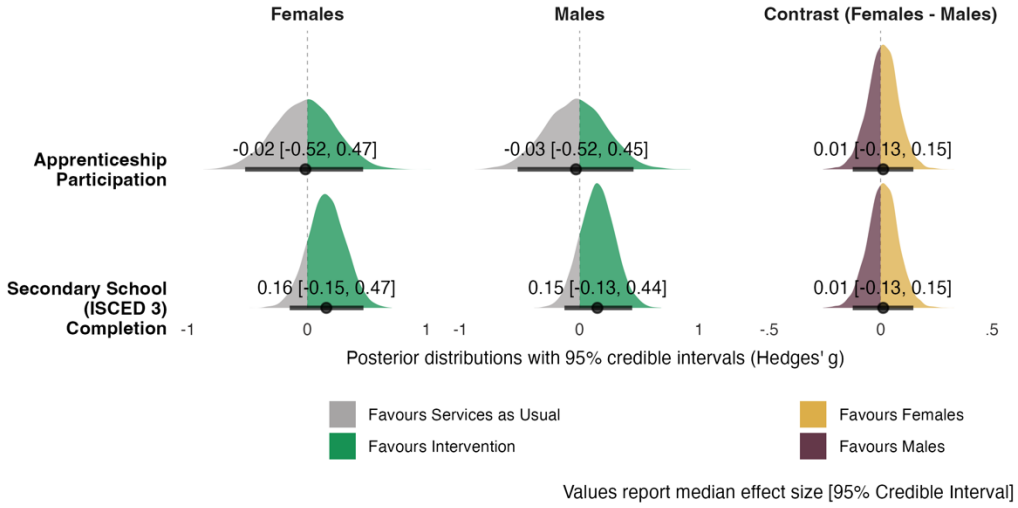


Figure 179 Impact of Wage Subsidies on Education and Skills



Public Works

Figure 180 Impact of Public Works on Labour Force status

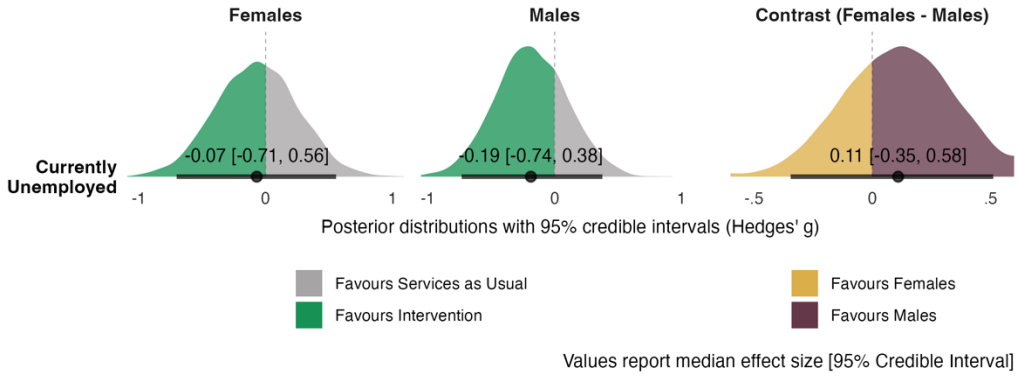


Figure 181 Impact of Public Works on Employment compensation

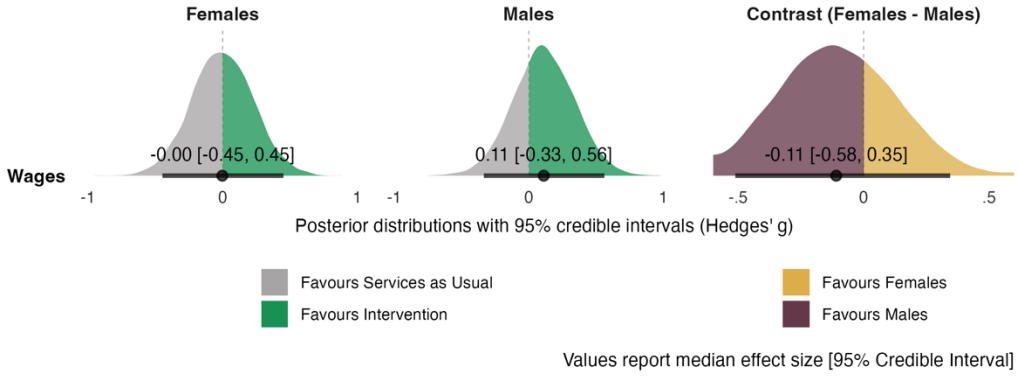


Figure 182 Impact of Public Works on Employment duration



Appendix C Subgroup analysis by age

This appendix presents subgroup effects by age. For each component x outcome combination, we show predicted effects at selected ages (16, 18, 20, 22, and 24 years). Each figure displays:

1. **Posterior distributions of effect sizes** — as with the main effects results, this shows the full range of plausible values for Hedges' *g*. Green shading indicates effects favouring the intervention component, while grey indicates effects favouring services as usual.
2. **Median and 95% CrI** — the central estimate (black dot) and the interval that contains 95% of the posterior probability.
3. **Age contrasts** — comparisons across rows illustrate how the estimated effect changes as the mean study age increases, allowing us to examine potential differences in effectiveness for younger versus older youth populations.

Consistent with the subgroup estimates by sex, these results should be interpreted with caution. The same caveats apply: they are observational rather than causal effects. Programmes enrolling younger or older participants may differ in other ways beyond age, and the apparent differences we observe could be confounded by unmeasured contextual or implementation factors. As with the sex contrasts, observed variations by age should be understood as component-level patterns rather than outcome-specific effects.

Basic Skills Training

Figure 183 Impact of Basic Skills Training on Labour Force status

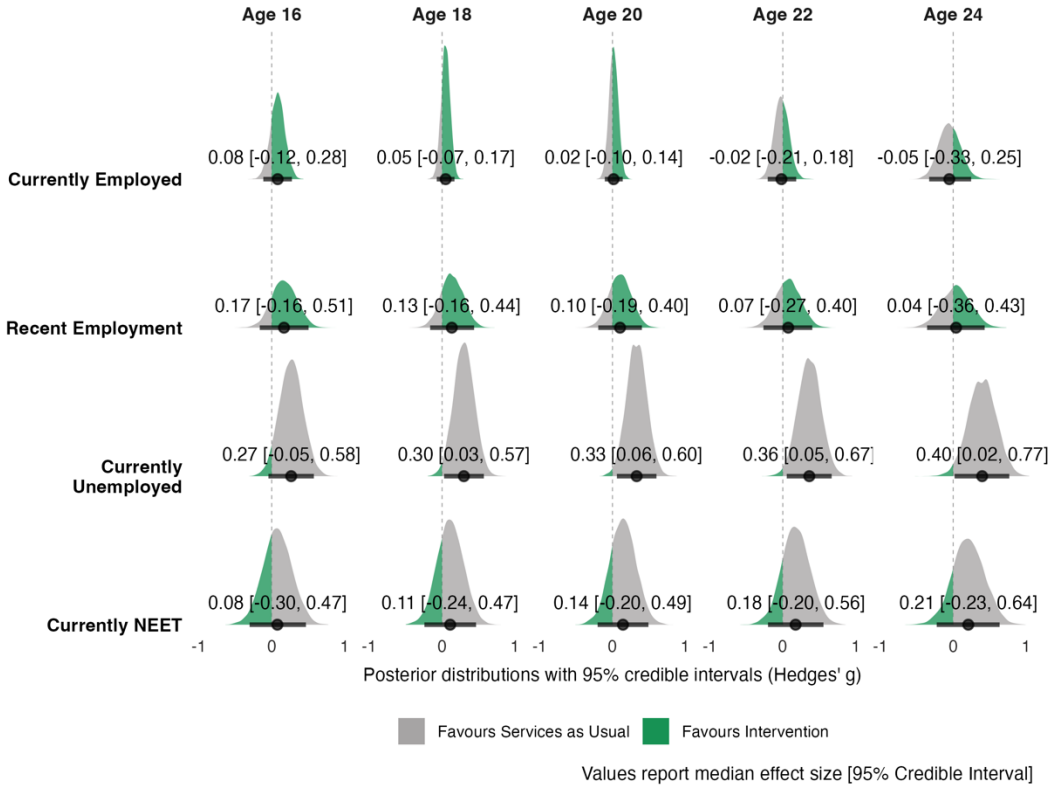


Figure 184 Impact of Basic Skills Training on Employment compensation

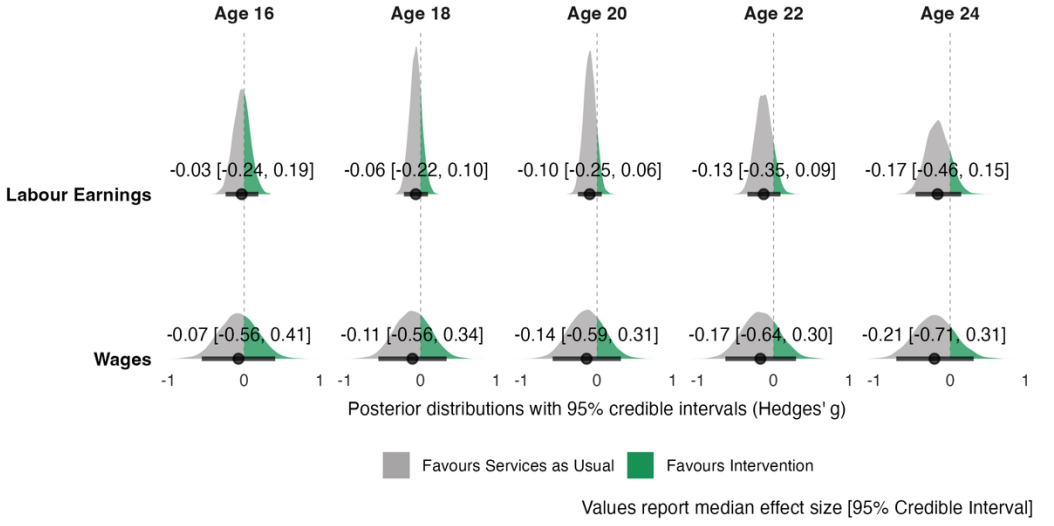


Figure 185 Impact of Basic Skills Training on Employment duration

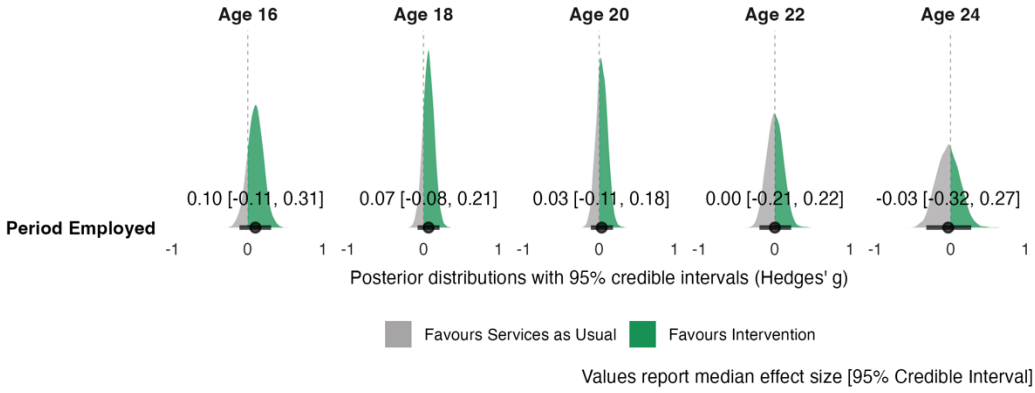


Figure 186 Impact of Basic Skills Training on Hours worked

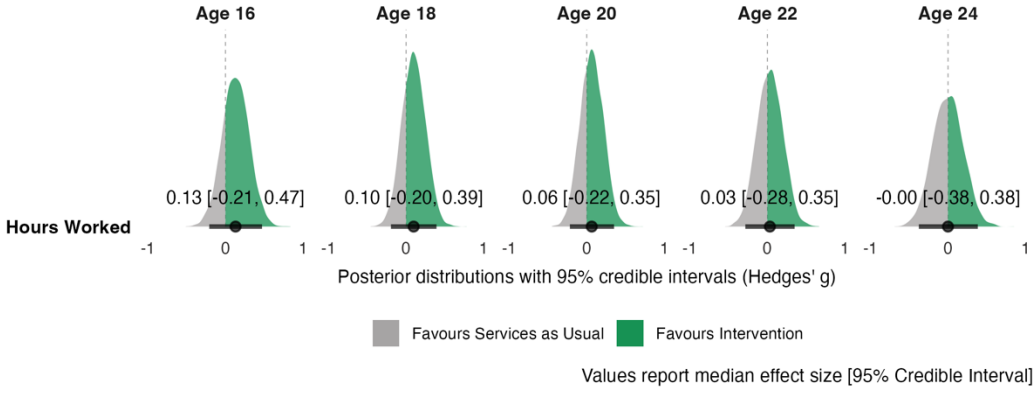
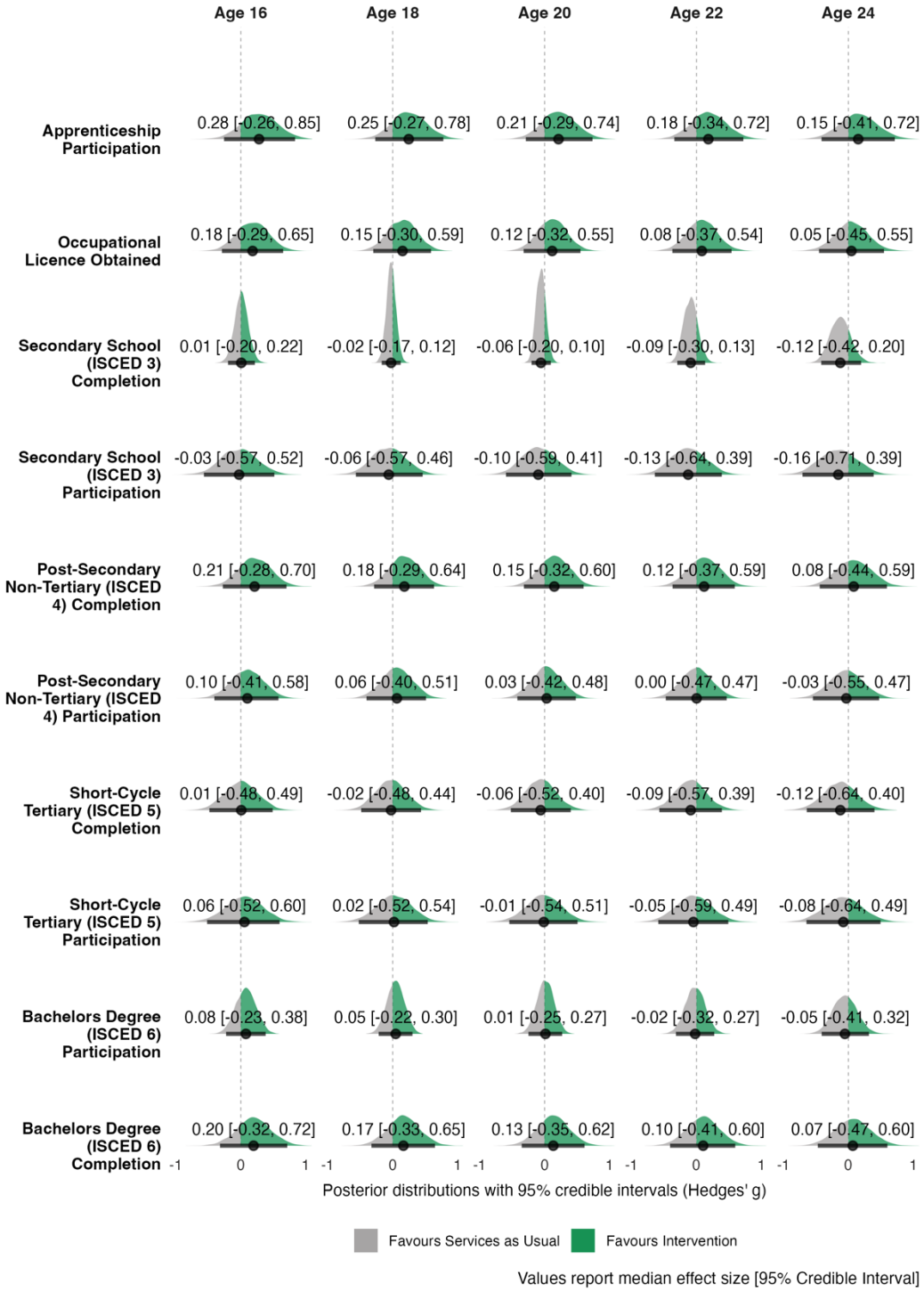


Figure 187 Impact of Basic Skills Training on Education and Skills



Soft Skills Training

Figure 188 Impact of Soft Skills Training on Labour Force status

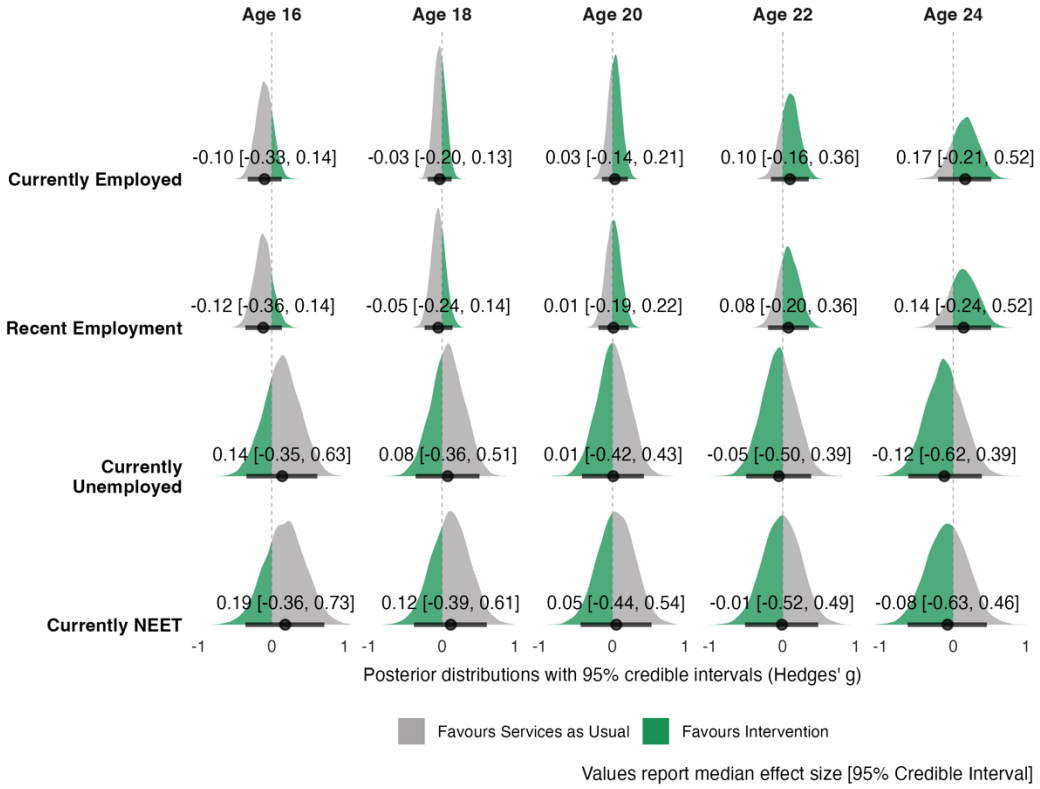


Figure 189 Impact of Soft Skills Training on Employment compensation

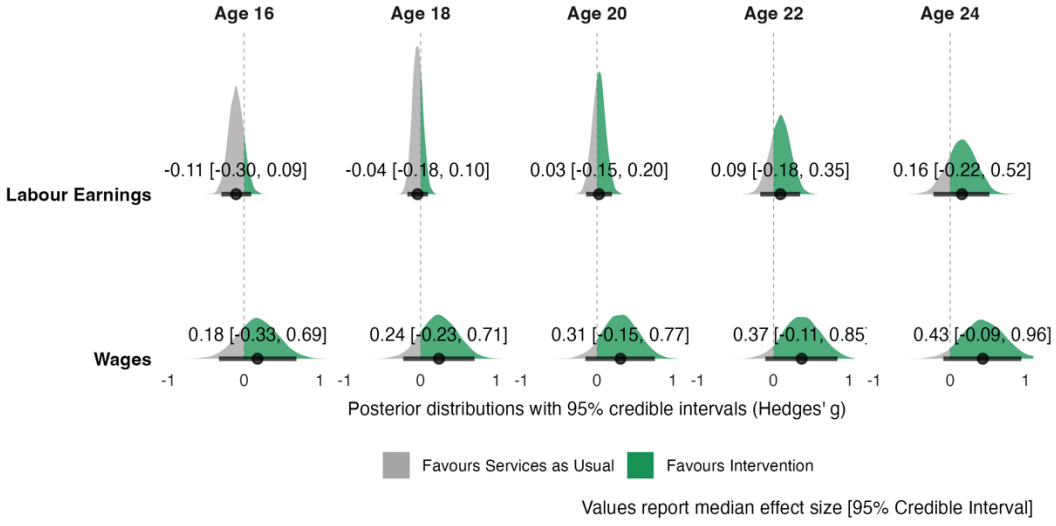


Figure 190 Impact of Soft Skills Training on Employment duration



Figure 191 Impact of Soft Skills Training on Hours worked

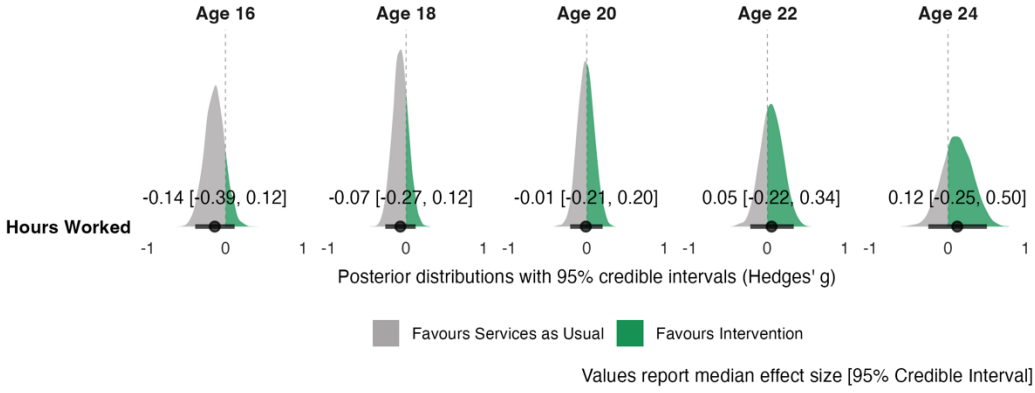
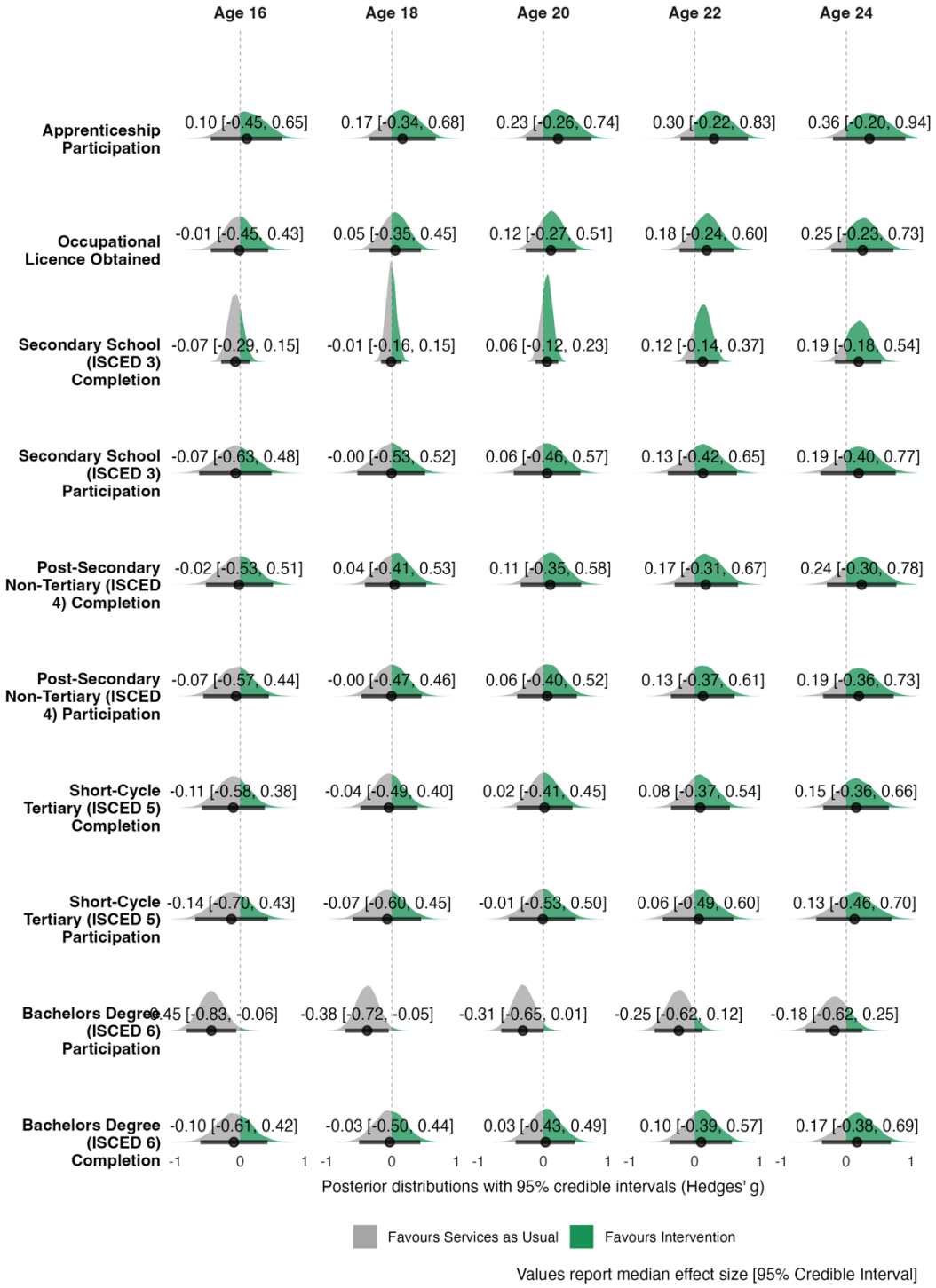


Figure 192 Impact of Soft Skills Training on Education and Skills



Behavioural Skills Training

Figure 193 Impact of Behavioural Skills Training on Labour Force status

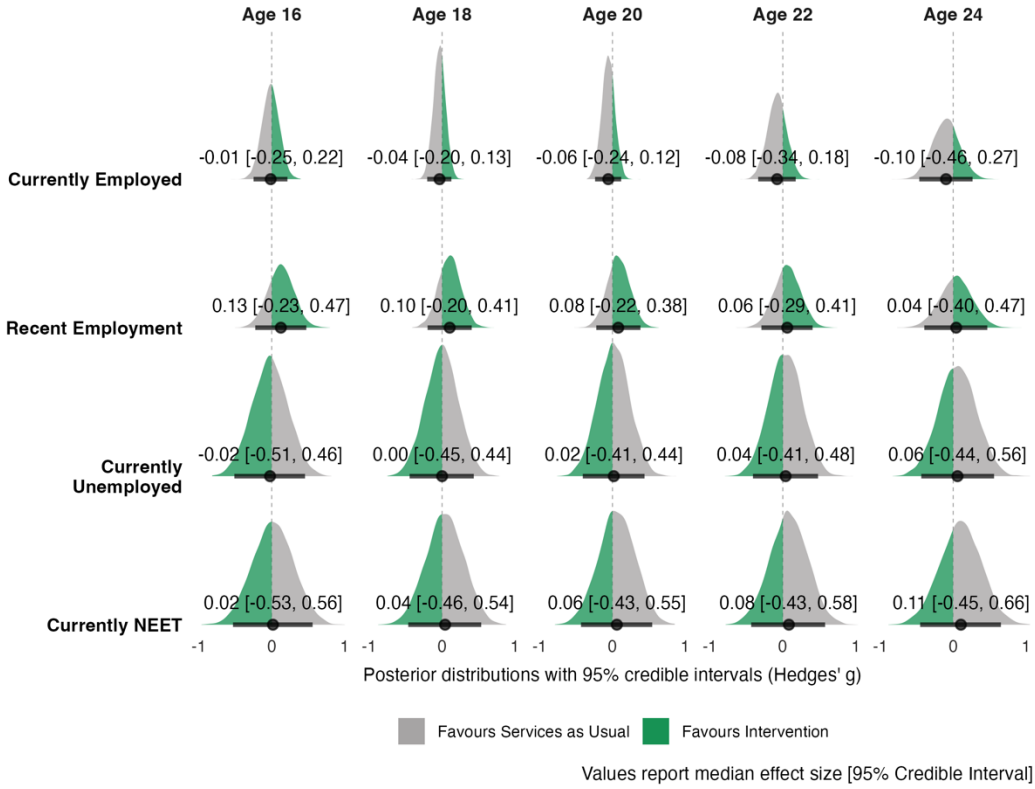


Figure 194 Impact of Behavioural Skills Training on Employment compensation

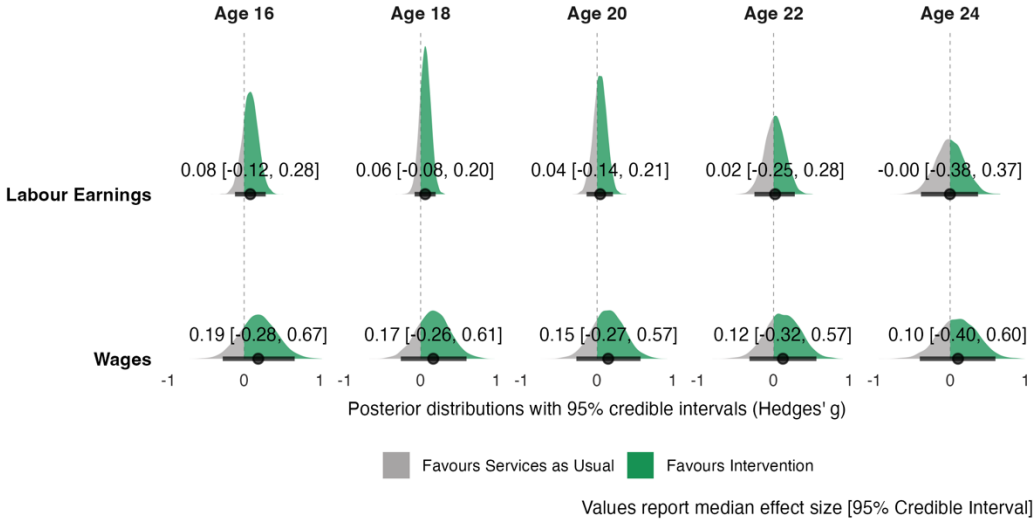


Figure 195 Impact of Behavioural Skills Training on Employment duration

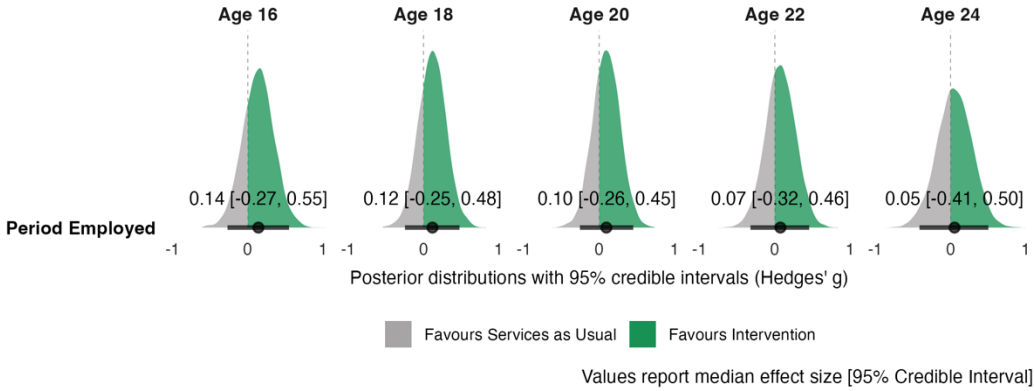


Figure 196 Impact of Behavioural Skills Training on Hours worked

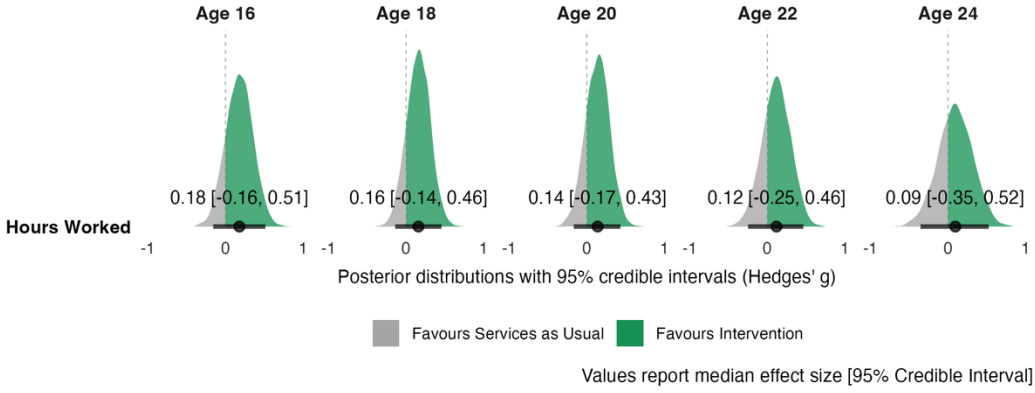
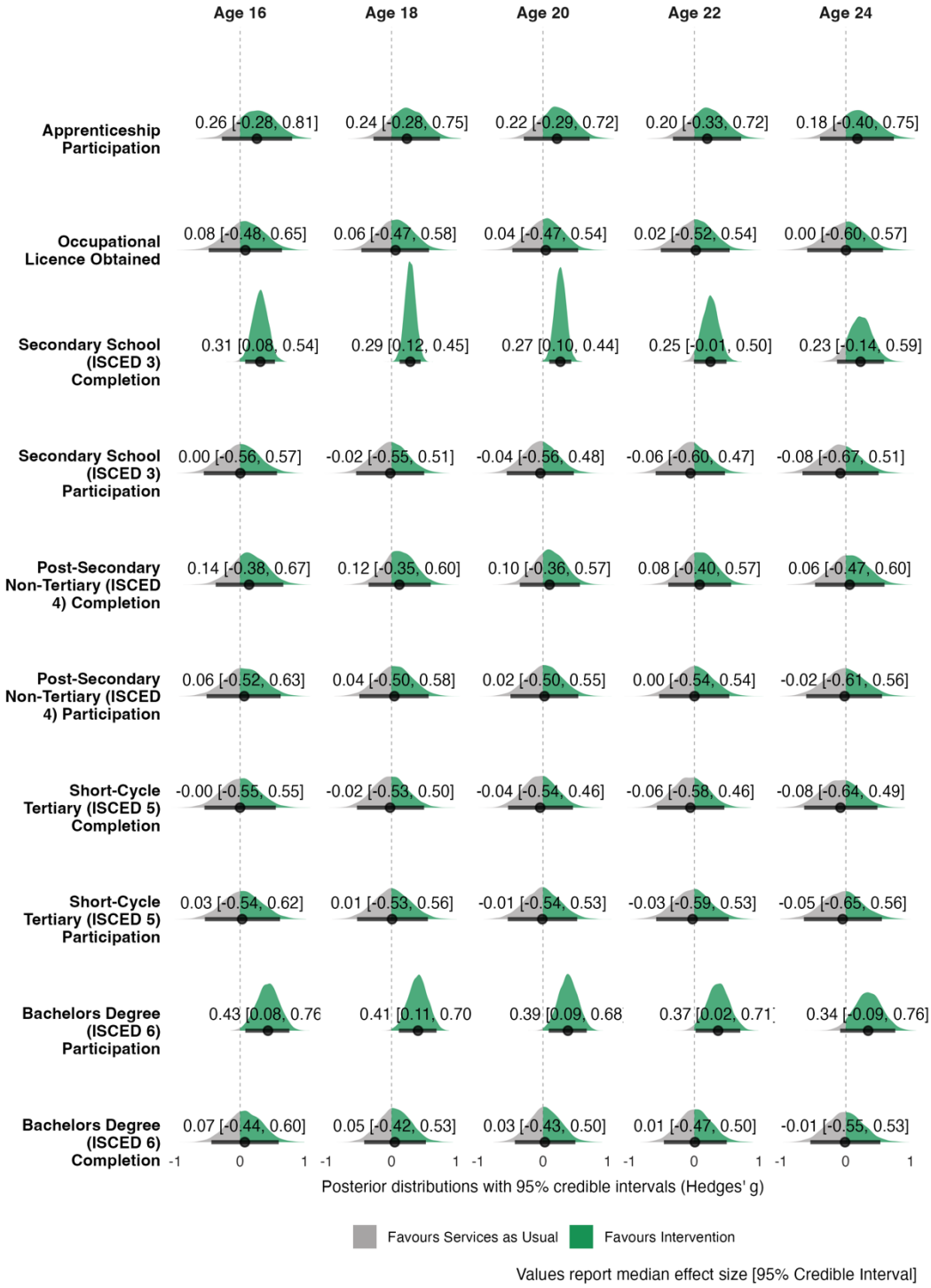


Figure 197 Impact of Behavioural Skills Training on Education and Skills



Job Specific Technical Skills (Off-Job Training)

Figure 198 Impact of Job Specific Technical Skills (Off-Job Training) on Labour Force status

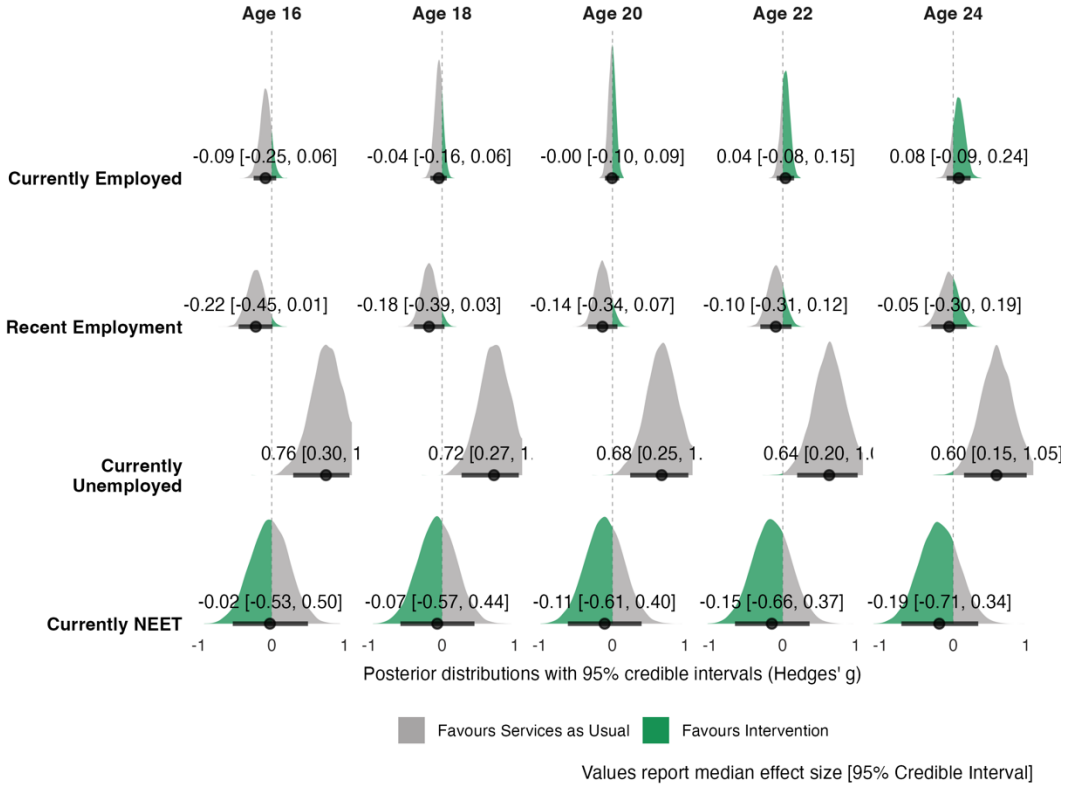


Figure 199 Impact of Job Specific Technical Skills (Off-Job Training) on Employment compensation

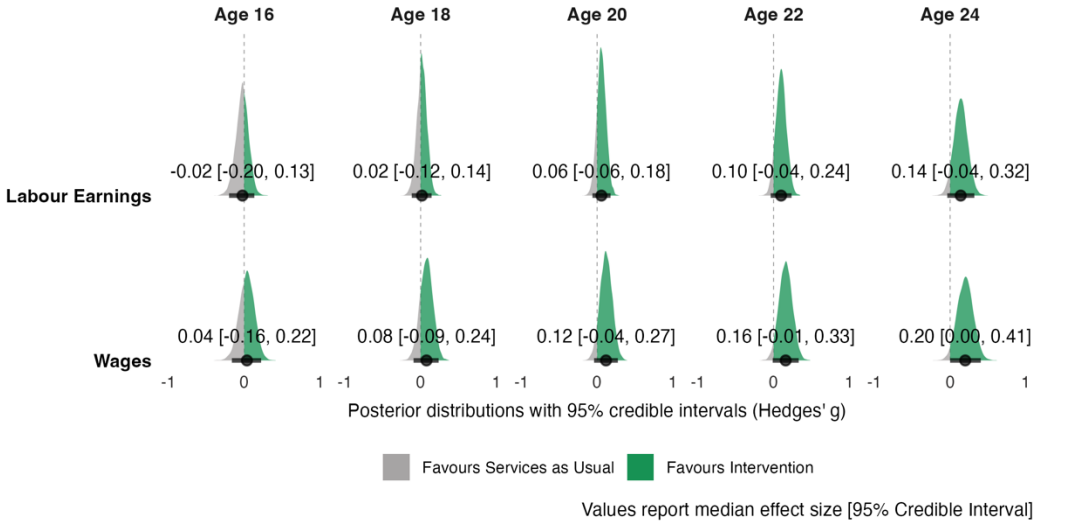


Figure 200 Impact of Job Specific Technical Skills (Off-Job Training) on Employment duration

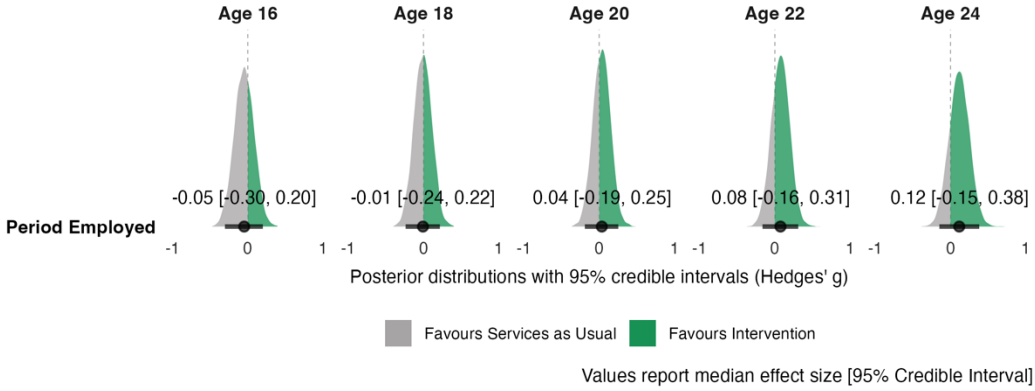


Figure 201 Impact of Job Specific Technical Skills (Off-Job Training) on Hours worked

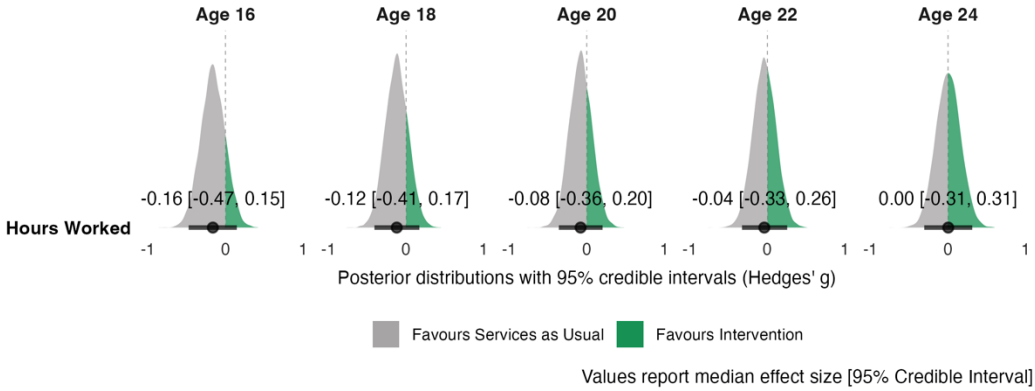
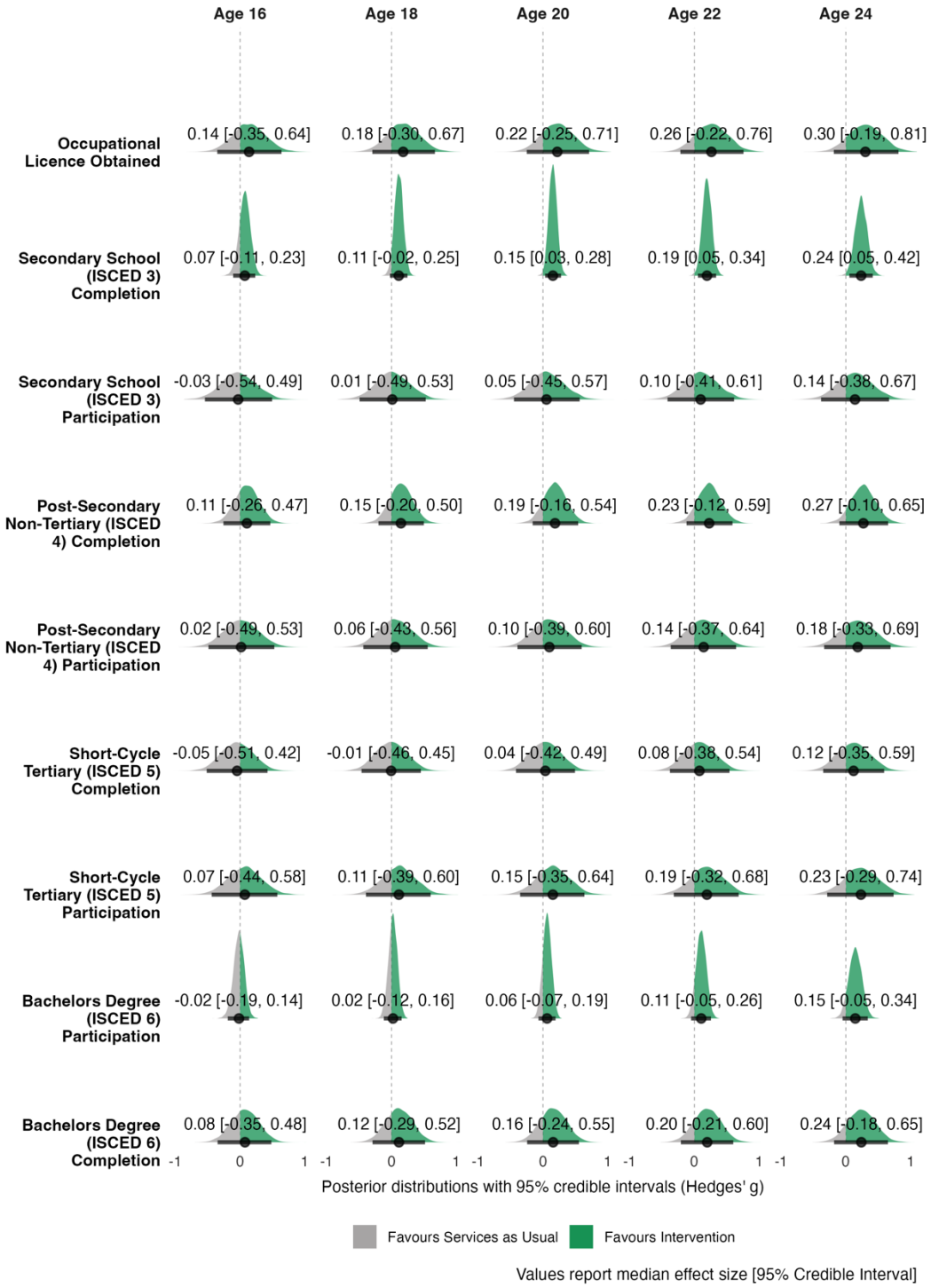


Figure 202 Impact of Job Specific Technical Skills (Off-Job Training) on Education and Skills



Self-Employment Support

Figure 203 Impact of Self-Employment Support on Labour Force status

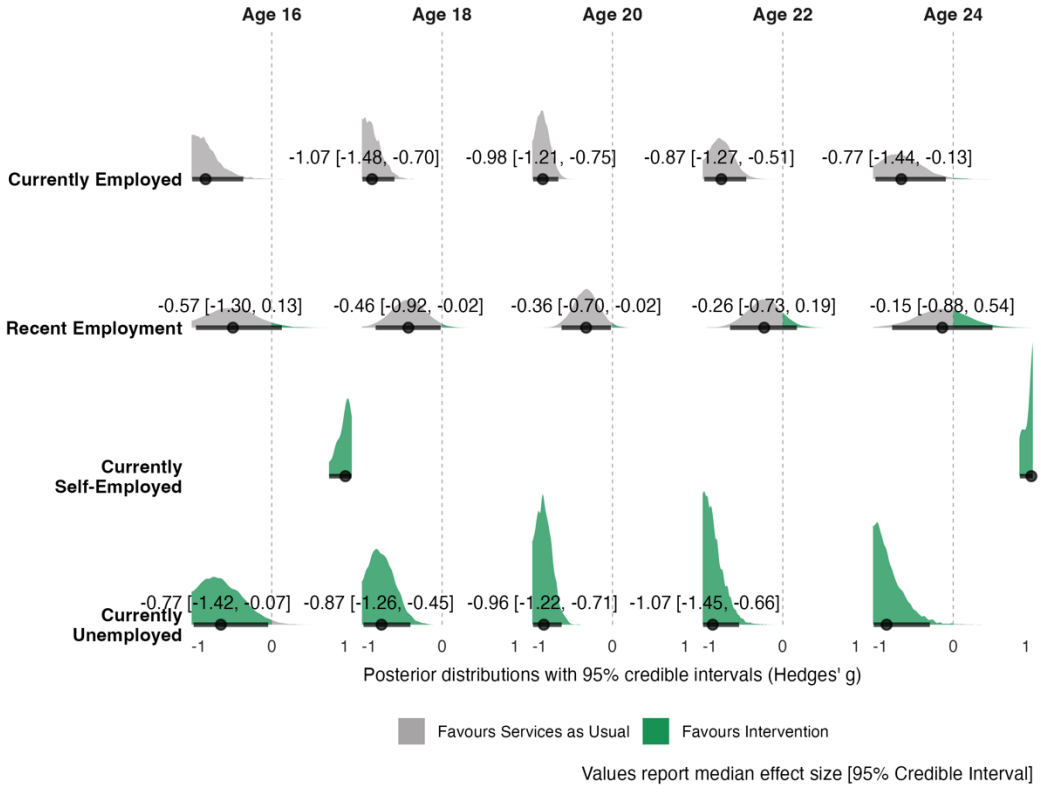


Figure 204 Impact of Self-Employment Support on Employment duration

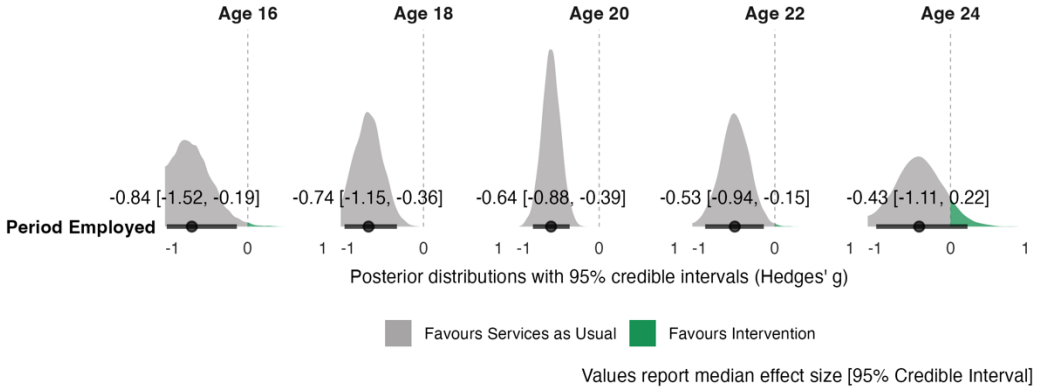
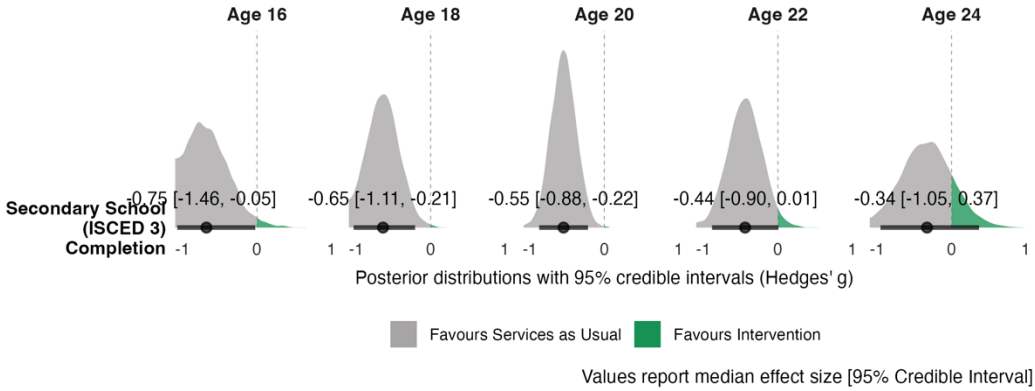


Figure 205 Impact of Self-Employment Support on Education and Skills



Job Search Preparation

Figure 206 Impact of Job Search Preparation on Labour Force status

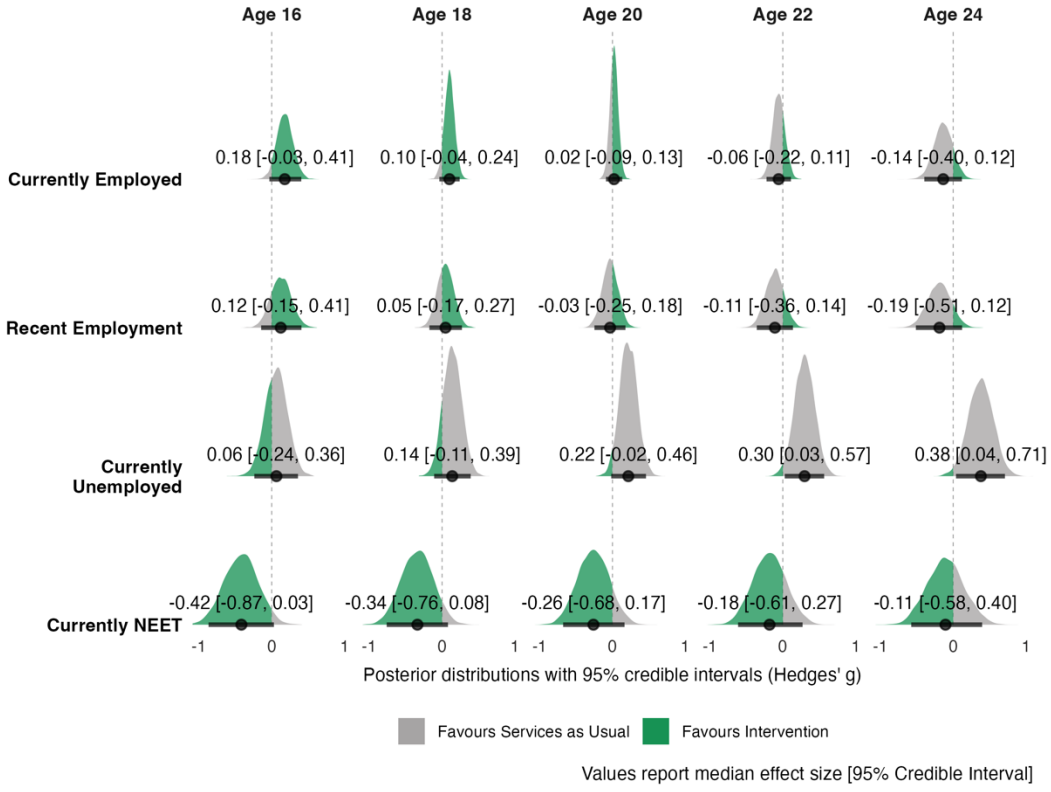


Figure 207 Impact of Job Search Preparation on Employment compensation

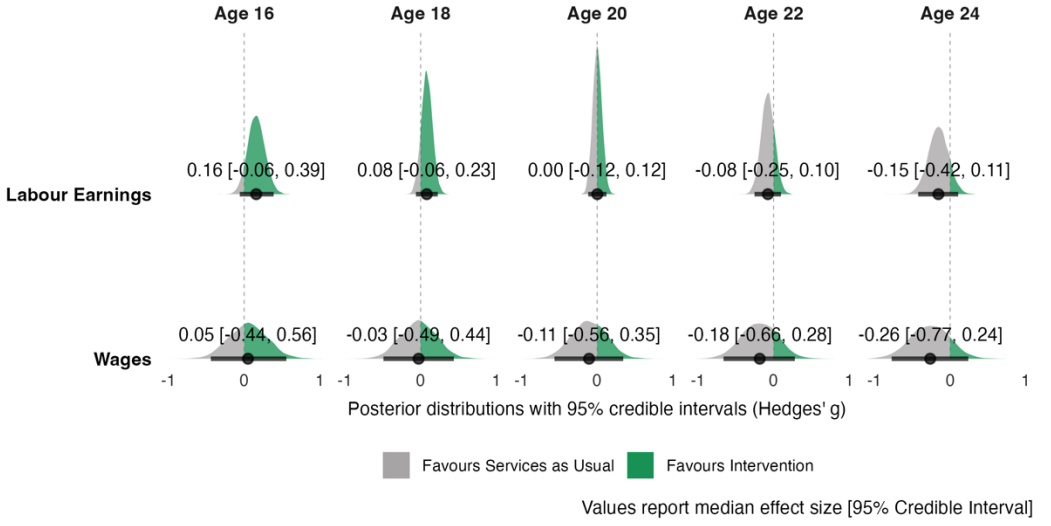


Figure 208 Impact of Job Search Preparation on Employment duration

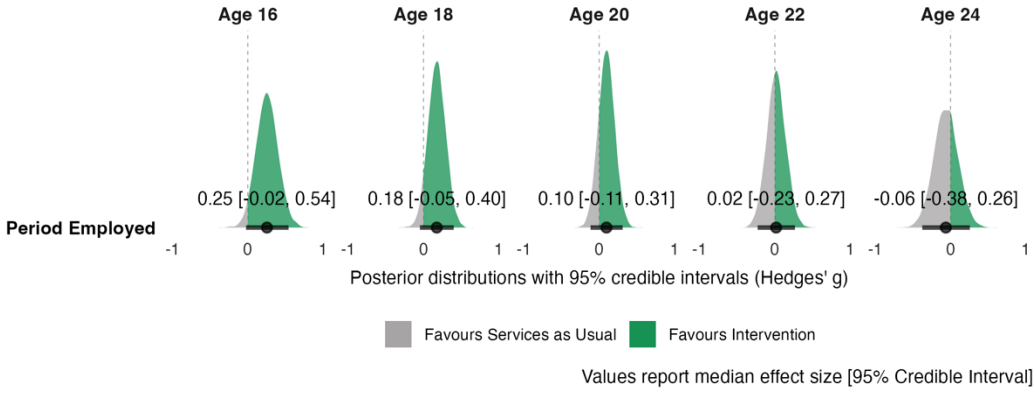


Figure 209 Impact of Job Search Preparation on Hours worked

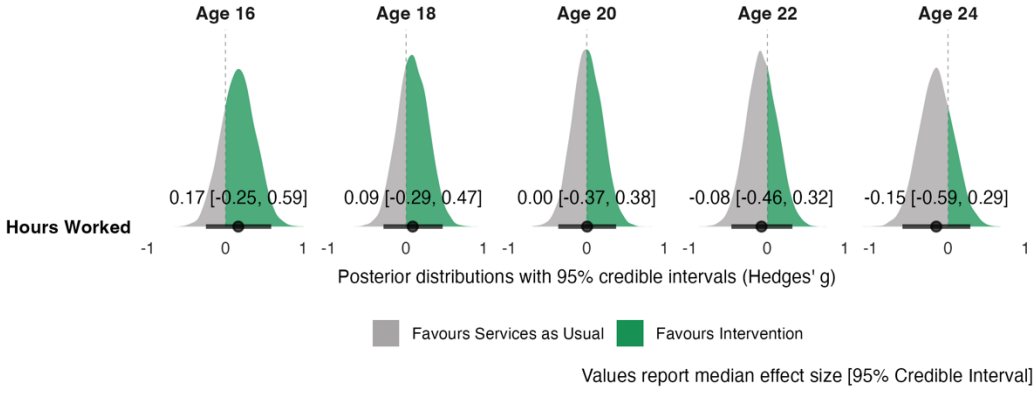
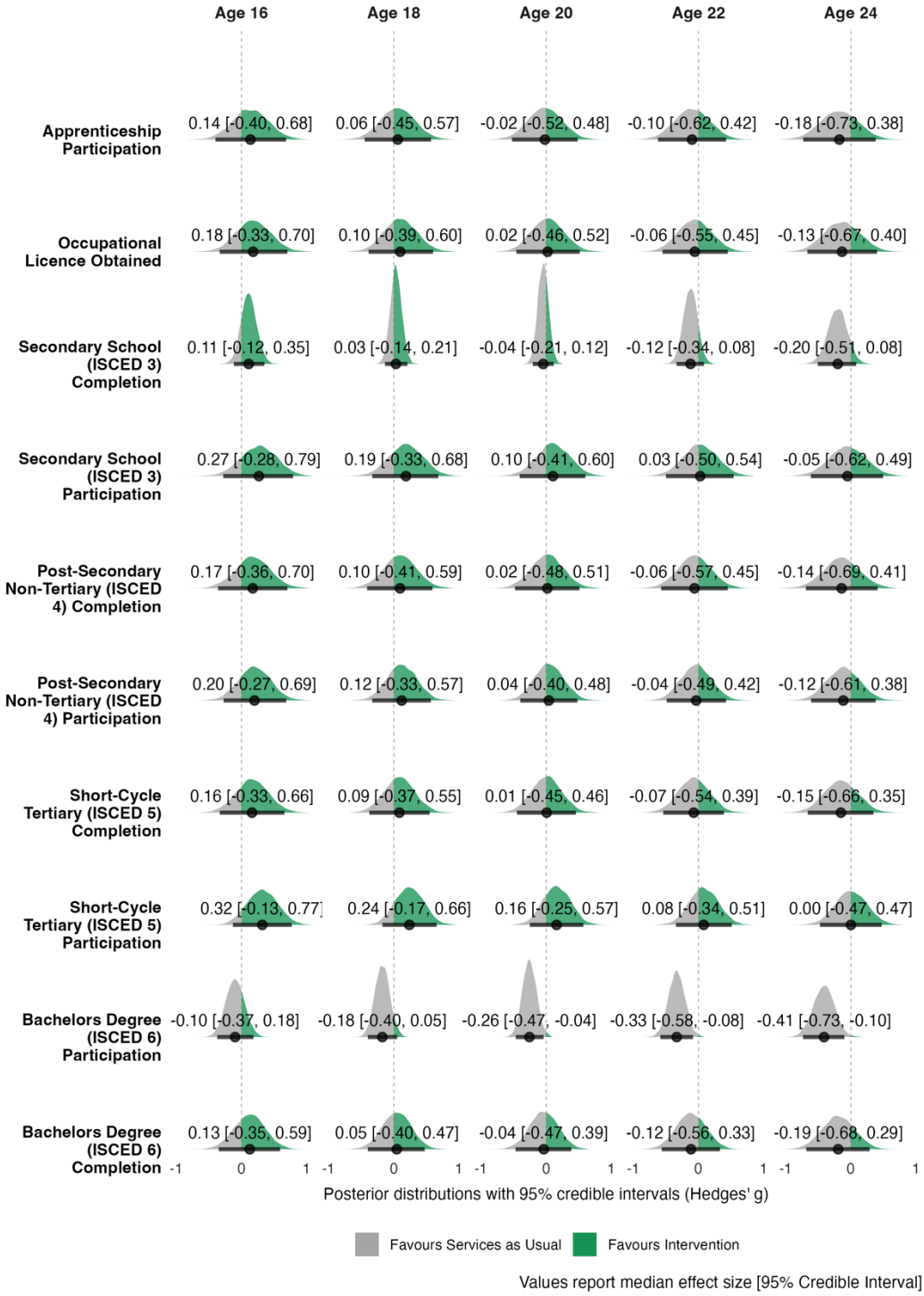


Figure 210 Impact of Job Search Preparation on Education and Skills



Job Search Assistance

Figure 211 Impact of Job Search Assistance on Labour Force status

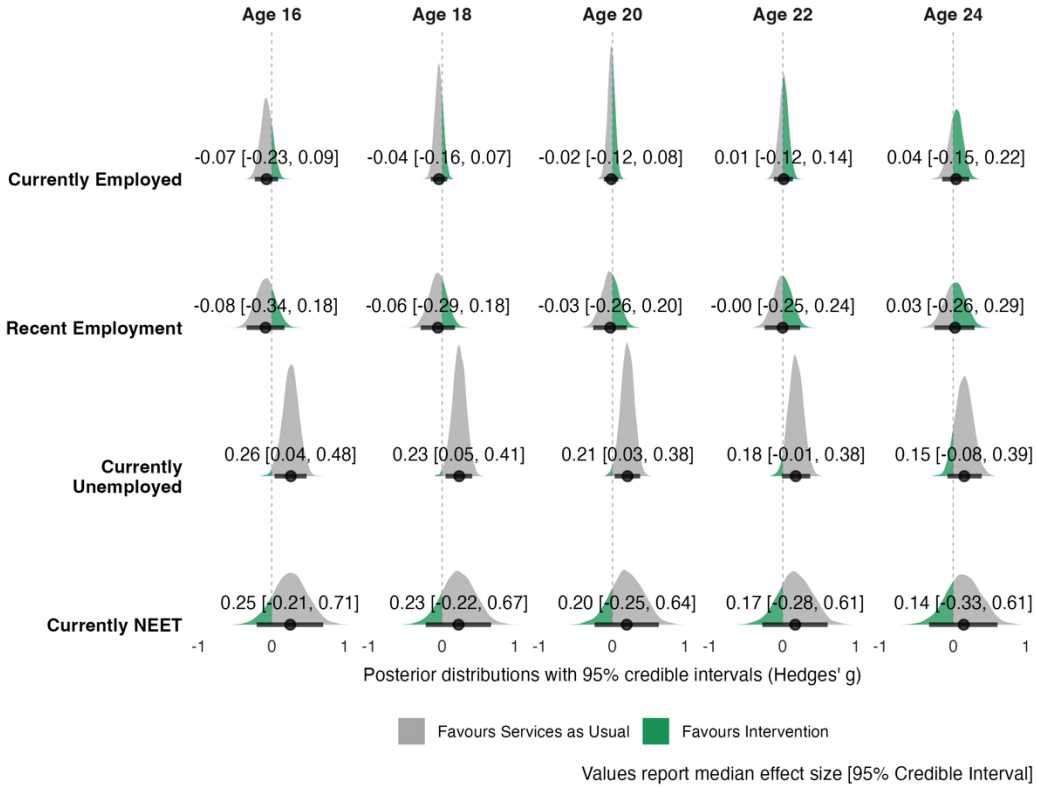


Figure 212 Impact of Job Search Assistance on Employment compensation

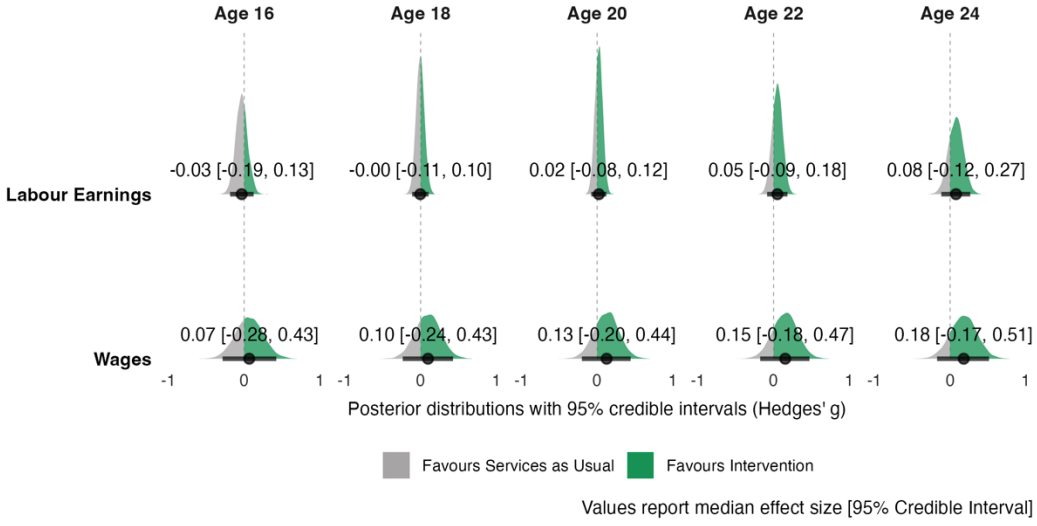


Figure 213 Impact of Job Search Assistance on Employment duration

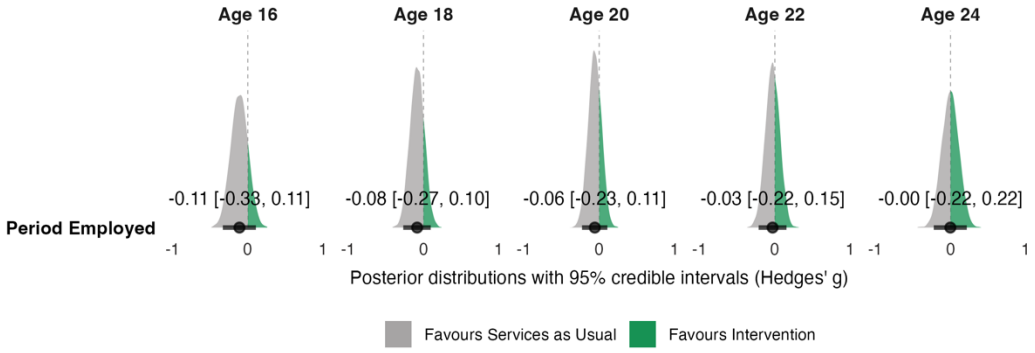


Figure 214 Impact of Job Search Assistance on Hours worked

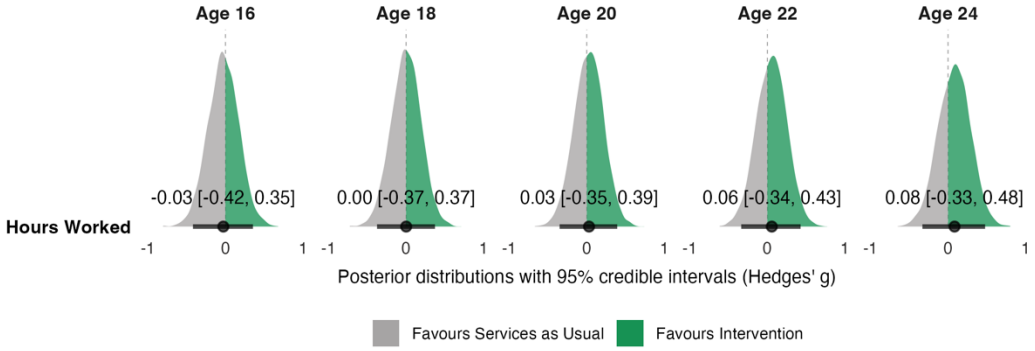
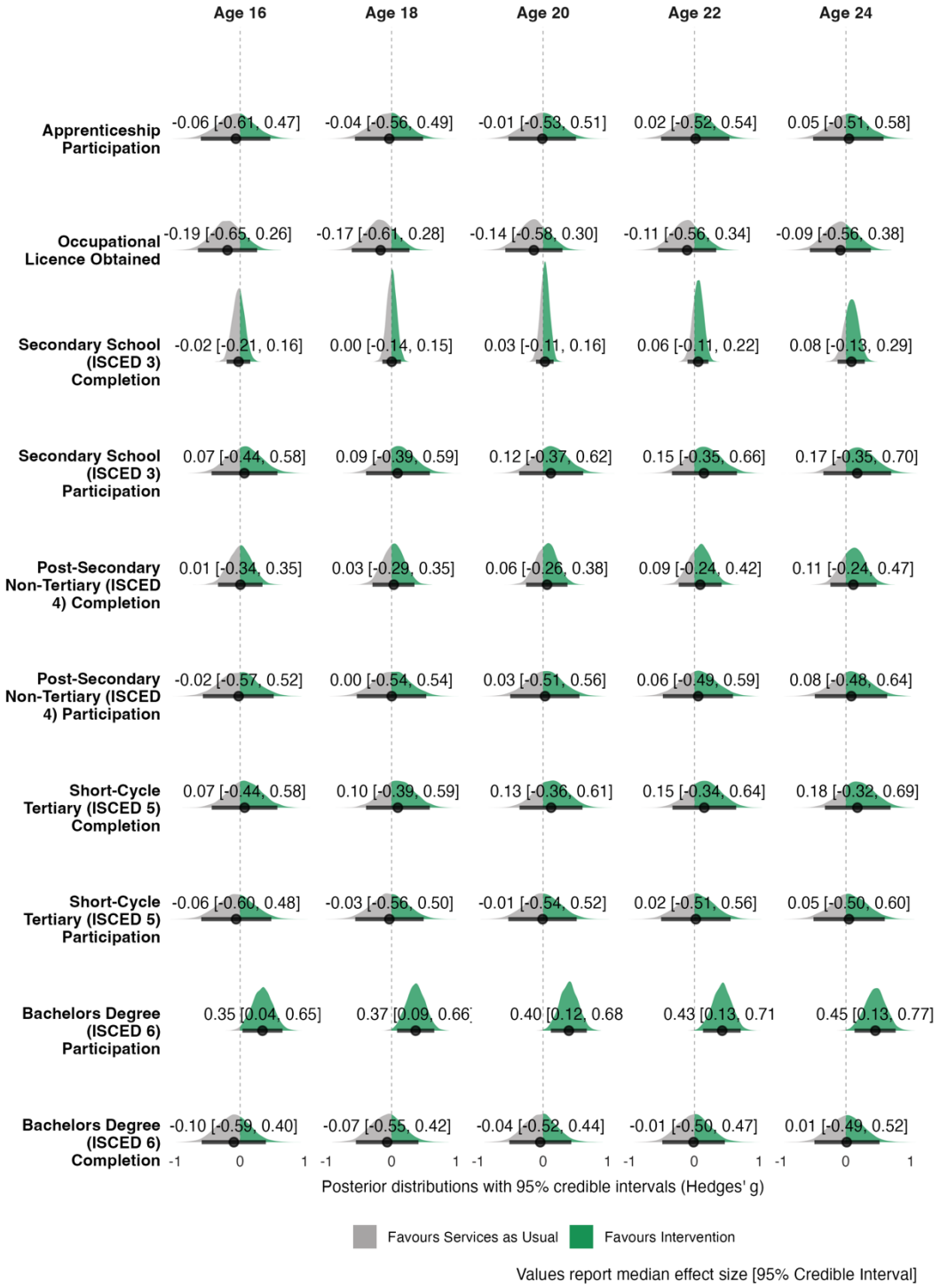


Figure 215 Impact of Job Search Assistance on Education and Skills



Employment Counselling

Figure 216 Impact of Employment Counselling on Labour Force status

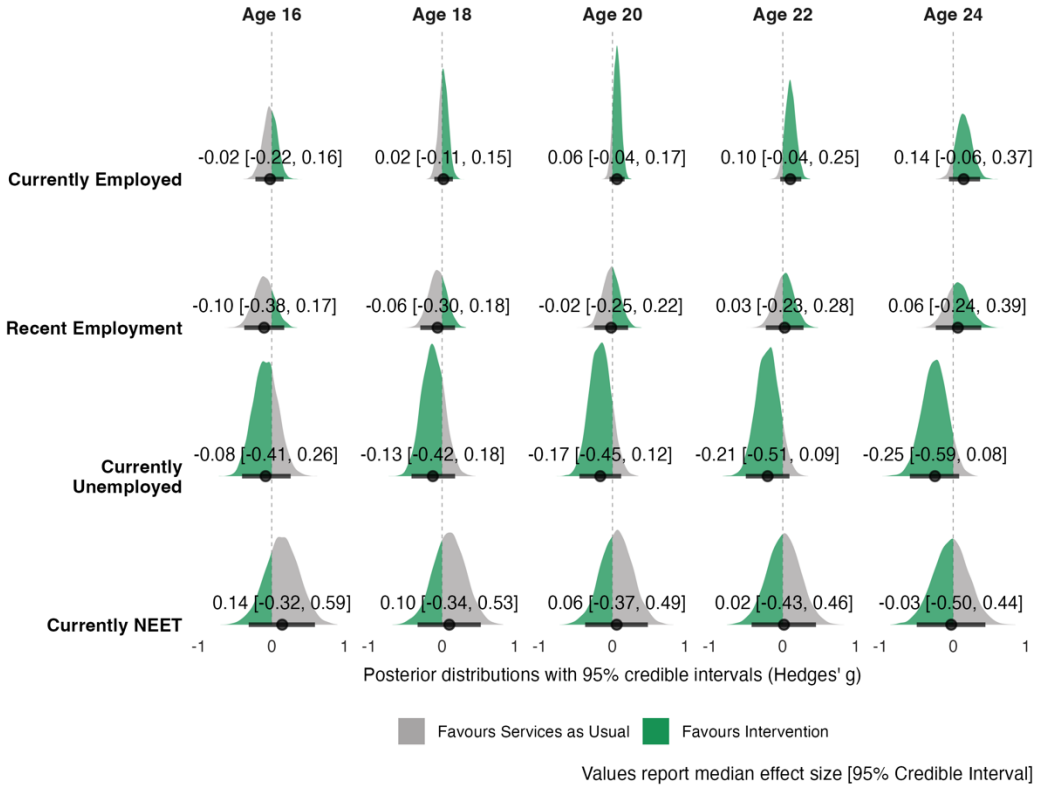


Figure 217 Impact of Employment Counselling on Employment compensation

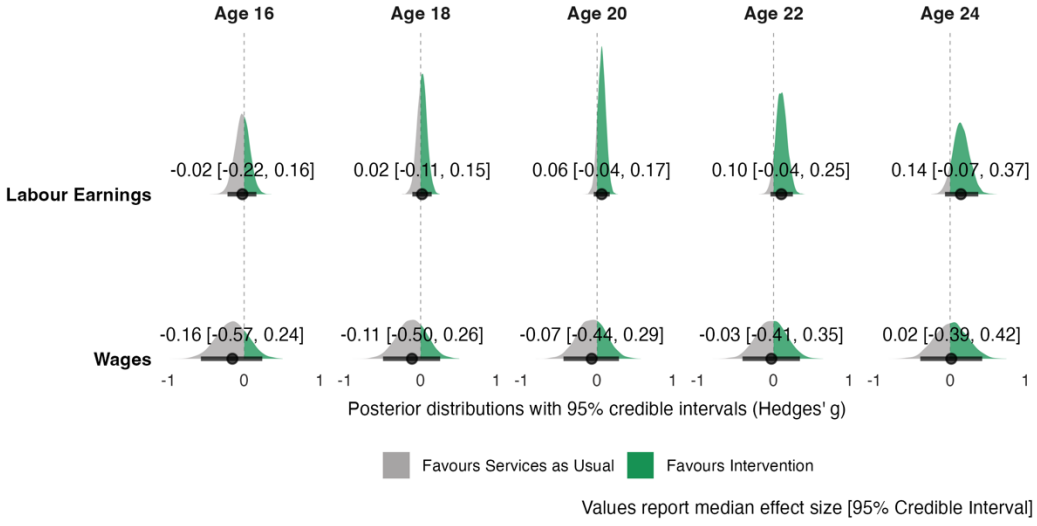


Figure 218 Impact of Employment Counselling on Employment duration

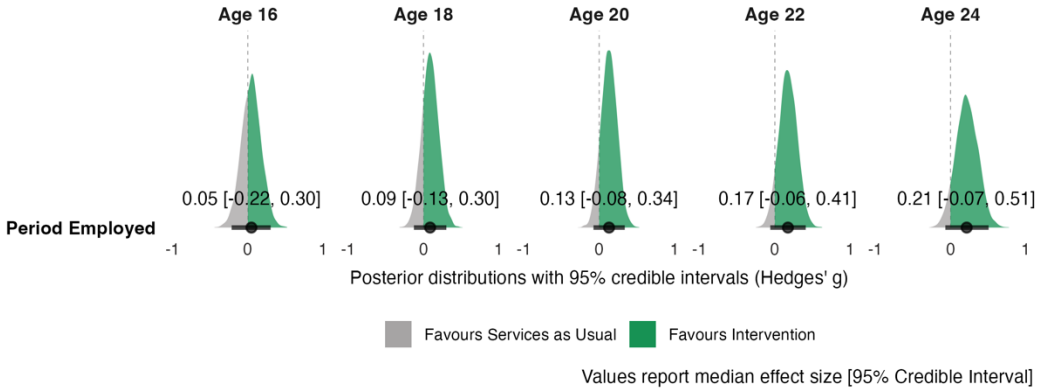


Figure 219 Impact of Employment Counselling on Hours worked

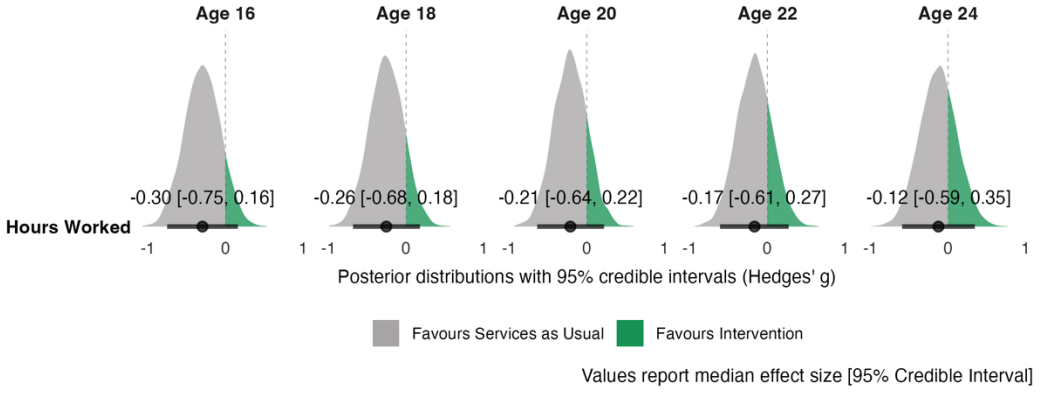
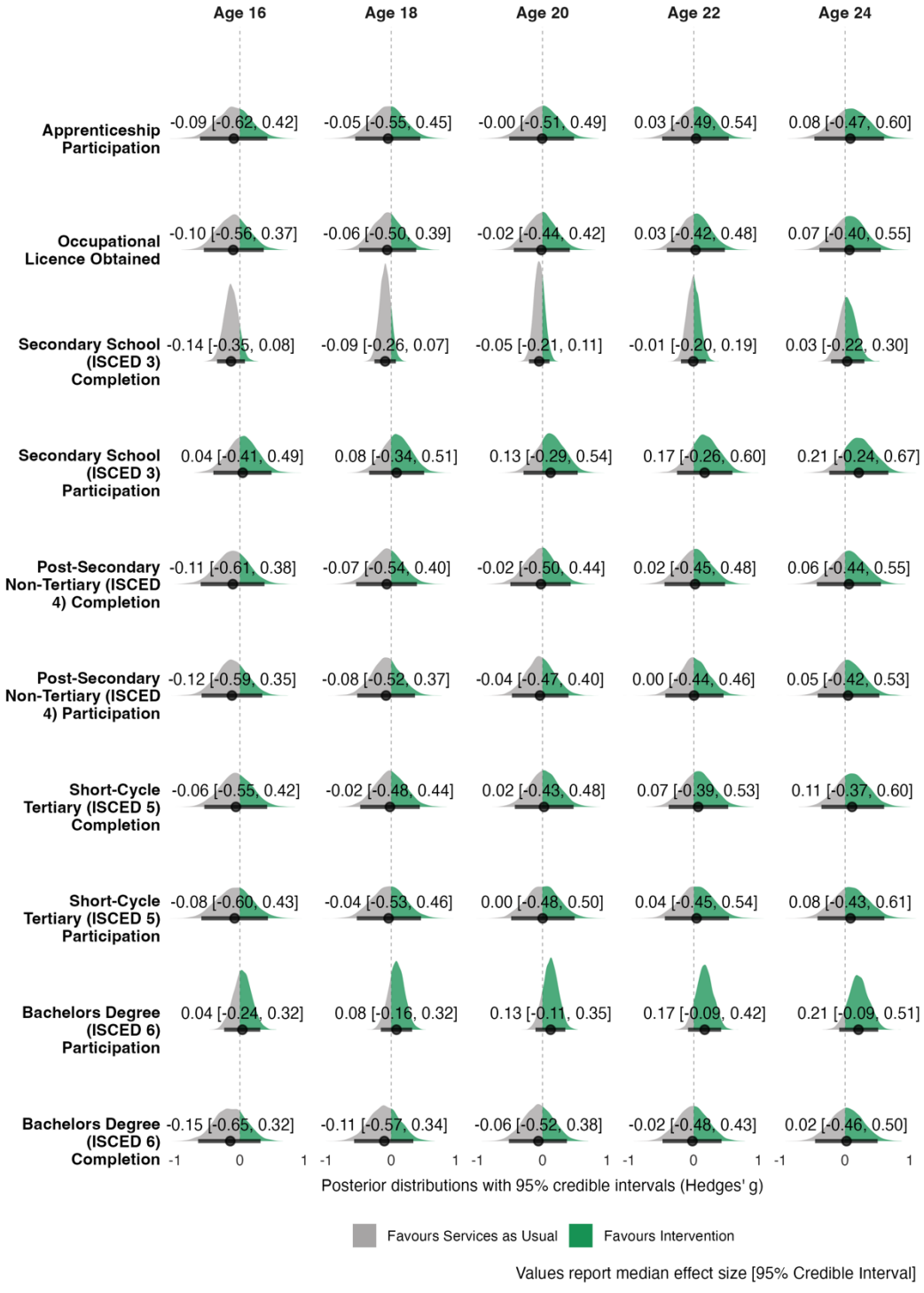


Figure 220 Impact of Employment Counselling on Education and Skills



Employment Coaching

Figure 221 Impact of Employment Coaching on Labour Force status

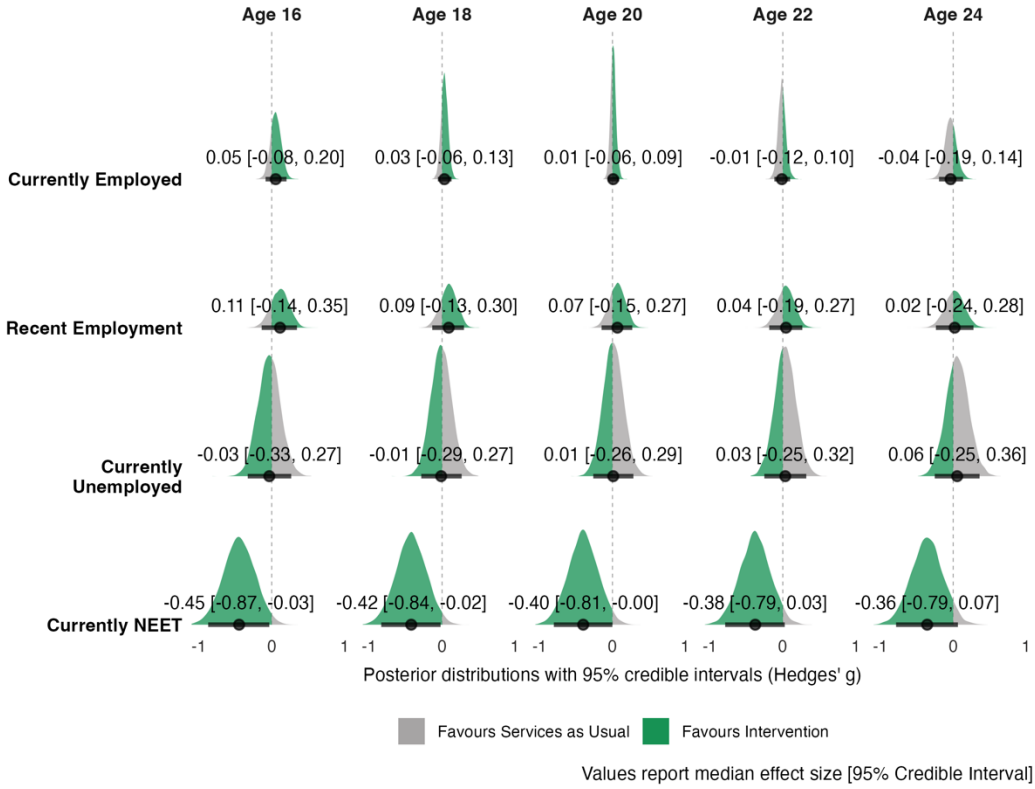


Figure 222 Impact of Employment Coaching on Employment compensation

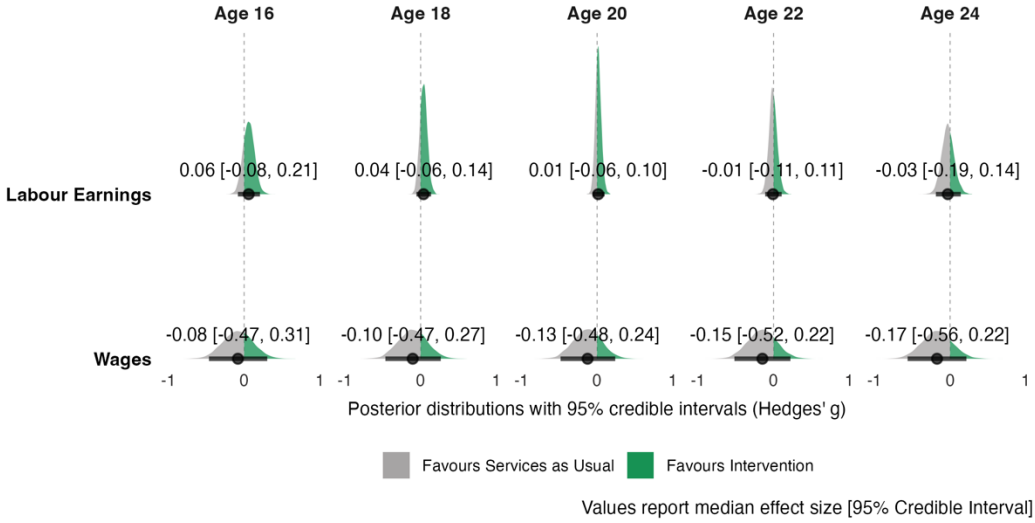


Figure 223 Impact of Employment Coaching on Employment duration

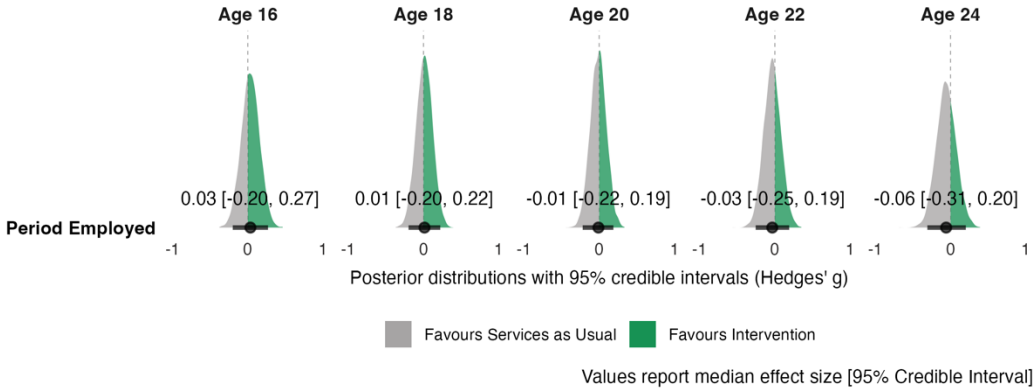


Figure 224 Impact of Employment Coaching on Hours worked

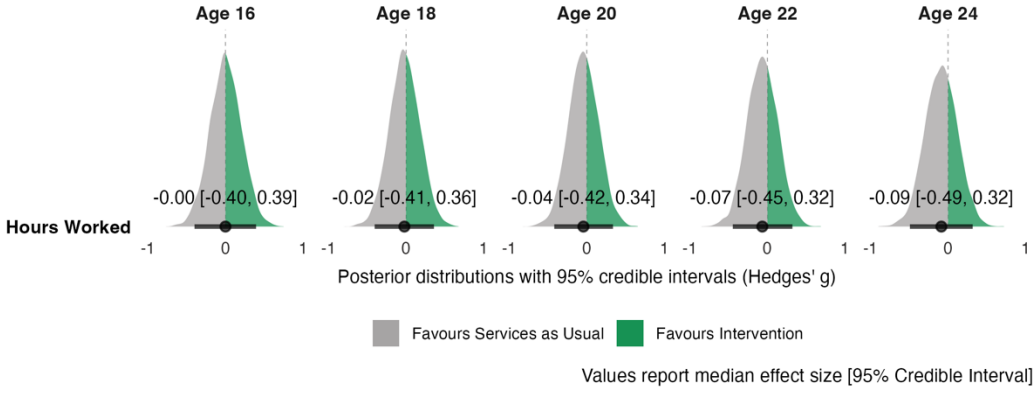
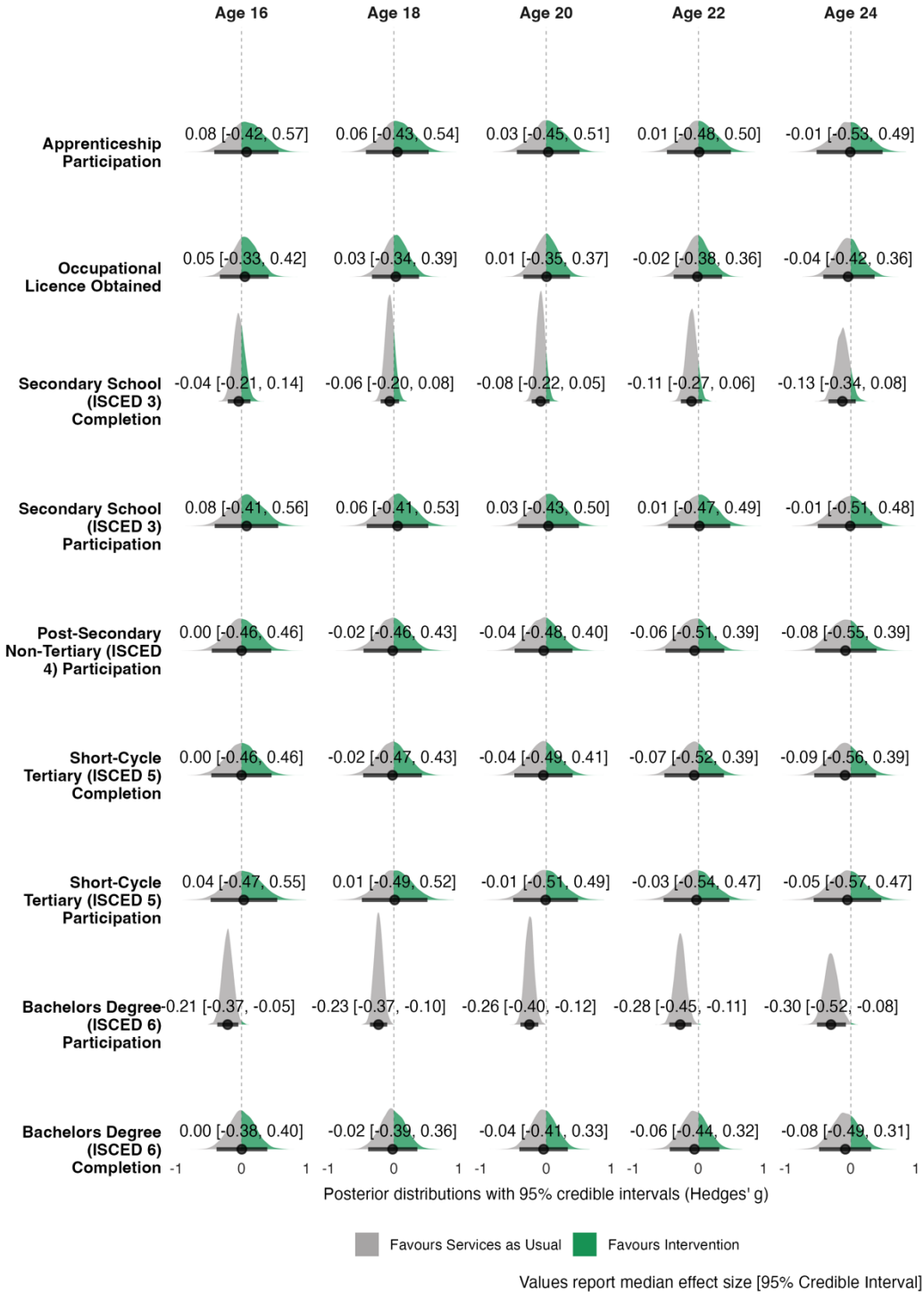


Figure 225 Impact of Employment Coaching on Education and Skills



Financial Assistance

Figure 226 Impact of Financial Assistance on Labour Force status

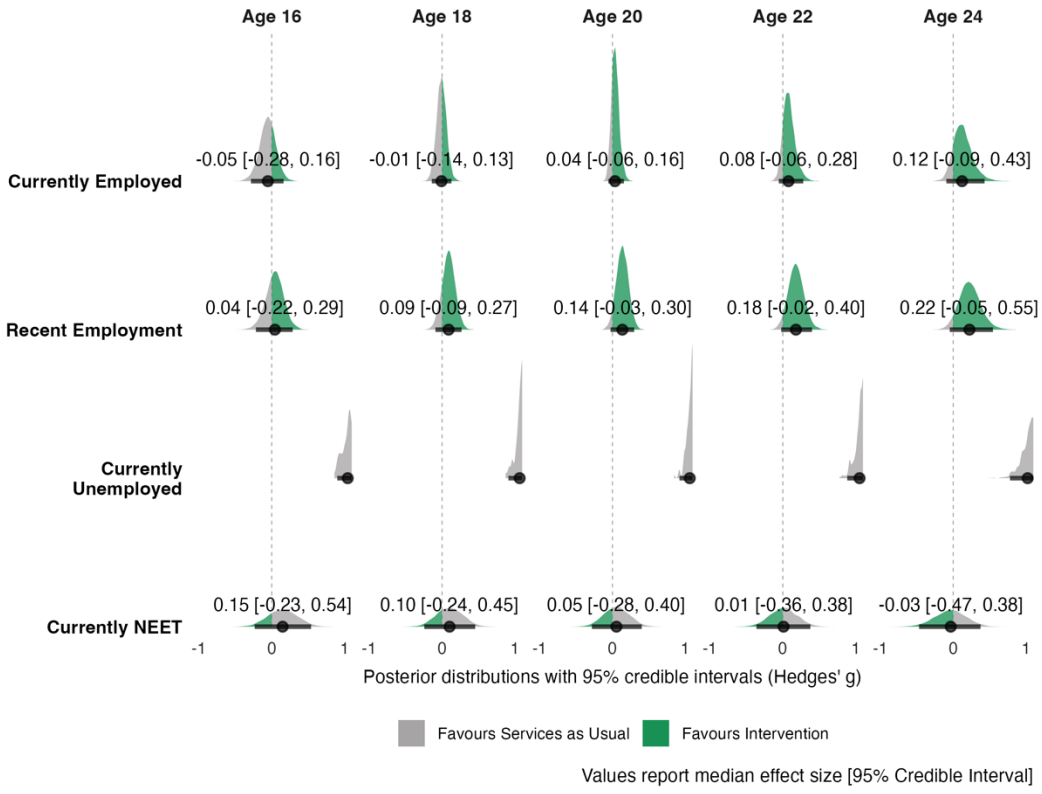


Figure 227 Impact of Financial Assistance on Employment compensation

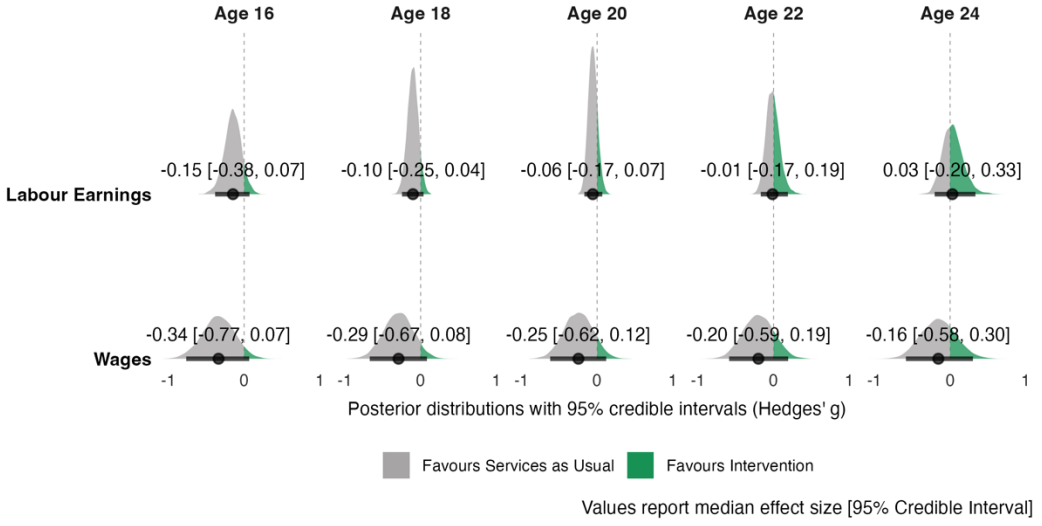


Figure 228 Impact of Financial Assistance on Employment duration

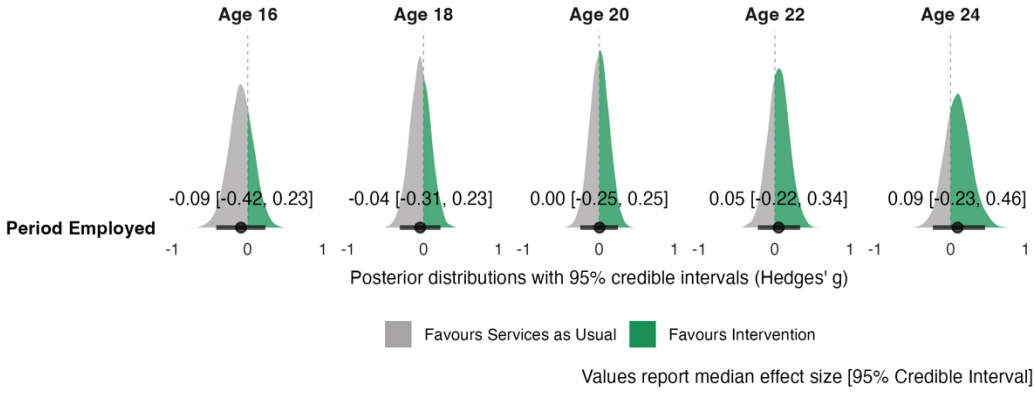


Figure 229 Impact of Financial Assistance on Hours worked

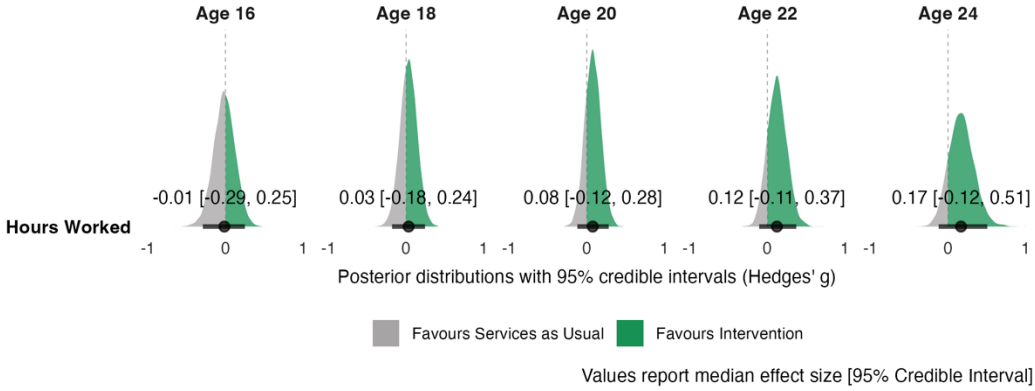
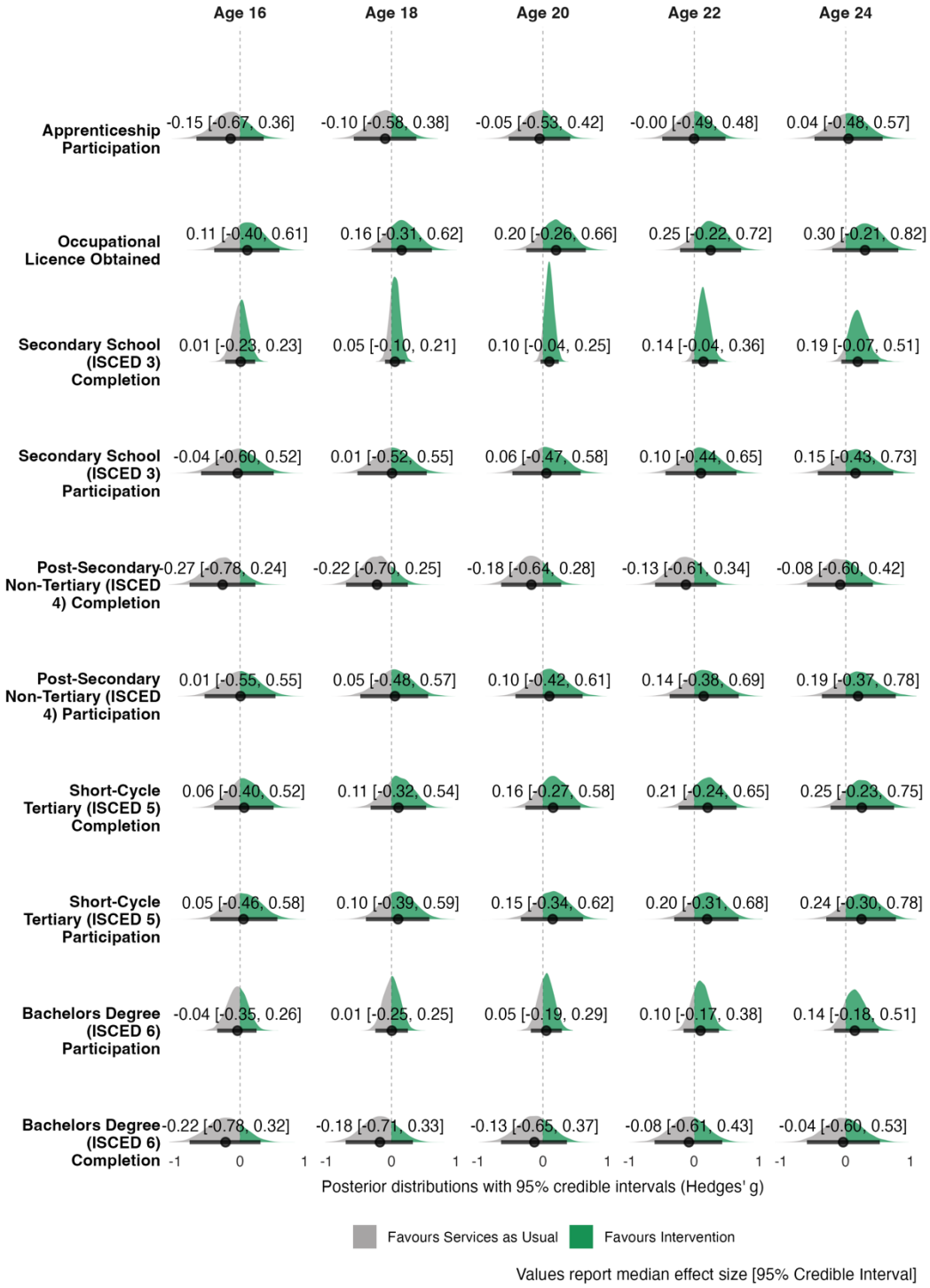


Figure 230 Impact of Financial Assistance on Education and Skills



Job Specific Technical Skills (On-Job Training)

Figure 231 Impact of Job Specific Technical Skills (On-Job Training) on Labour Force status

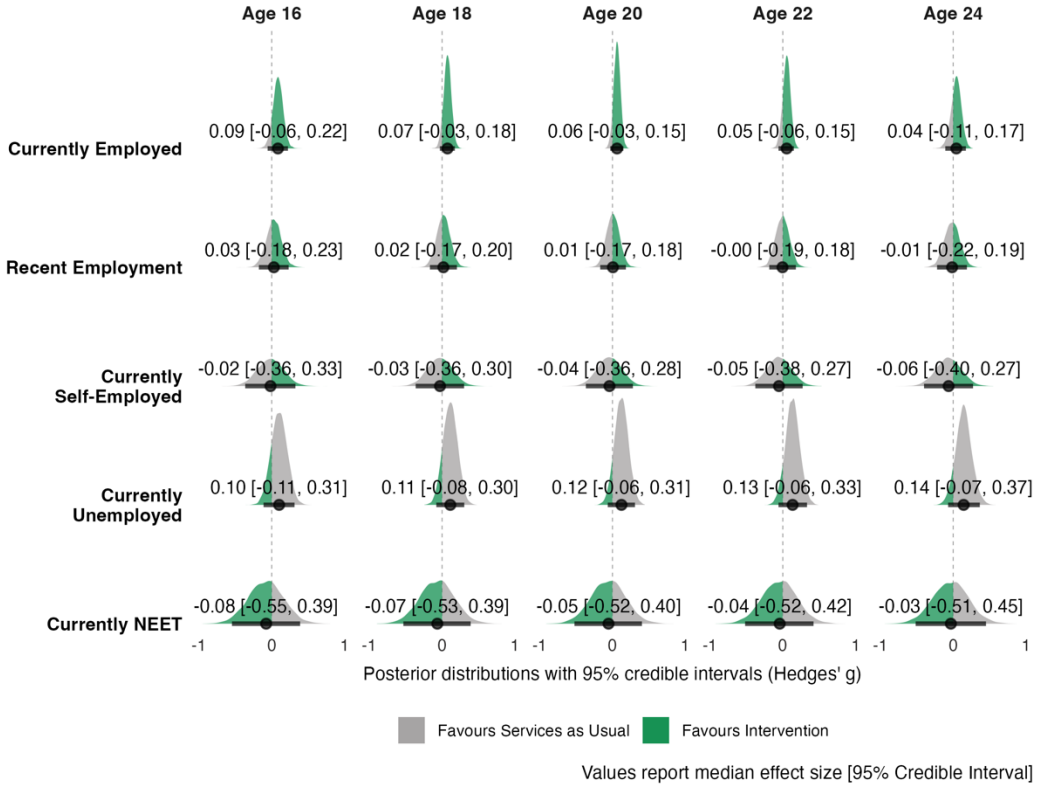


Figure 232 Impact of Job Specific Technical Skills (On-Job Training) on Employment compensation

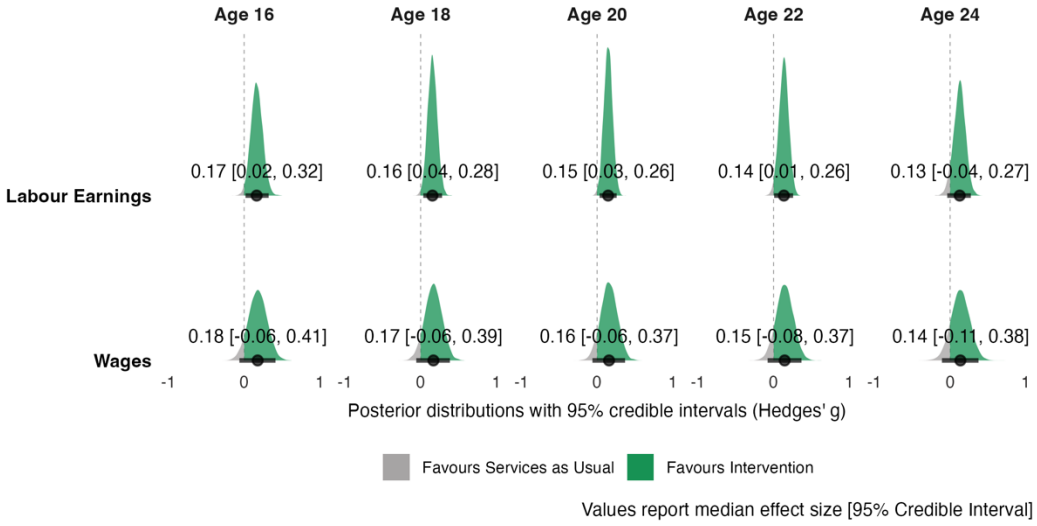


Figure 233 Impact of Job Specific Technical Skills (On-Job Training) on Employment duration

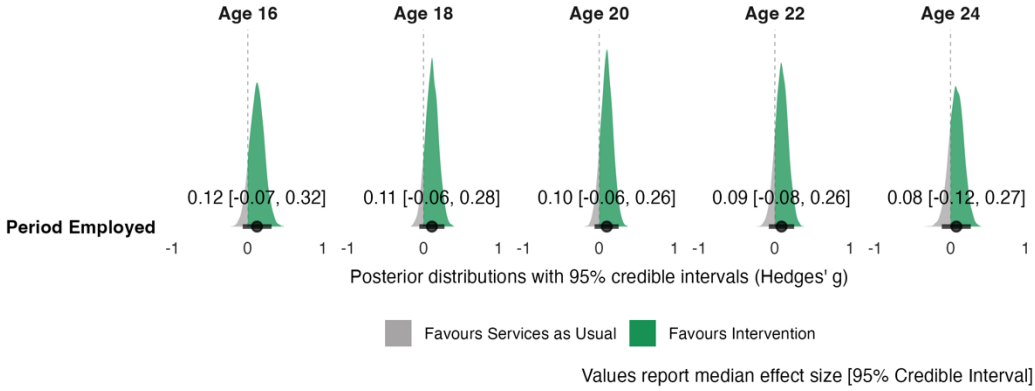


Figure 234 Impact of Job Specific Technical Skills (On-Job Training) on Hours worked

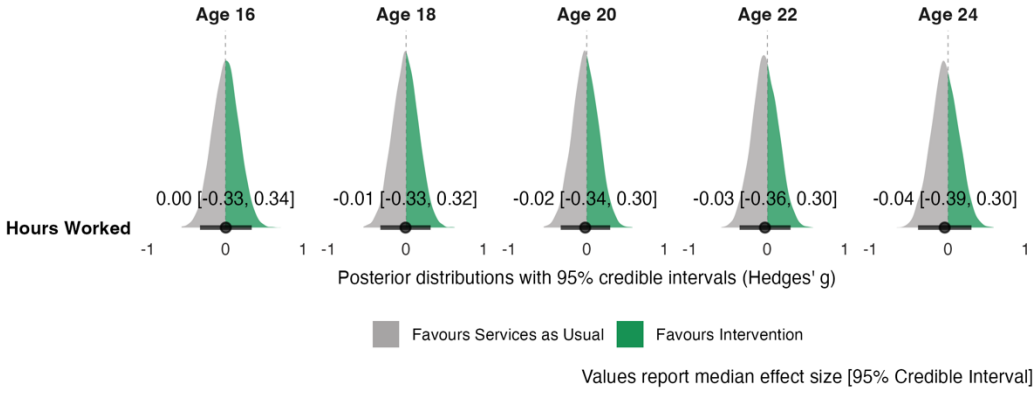
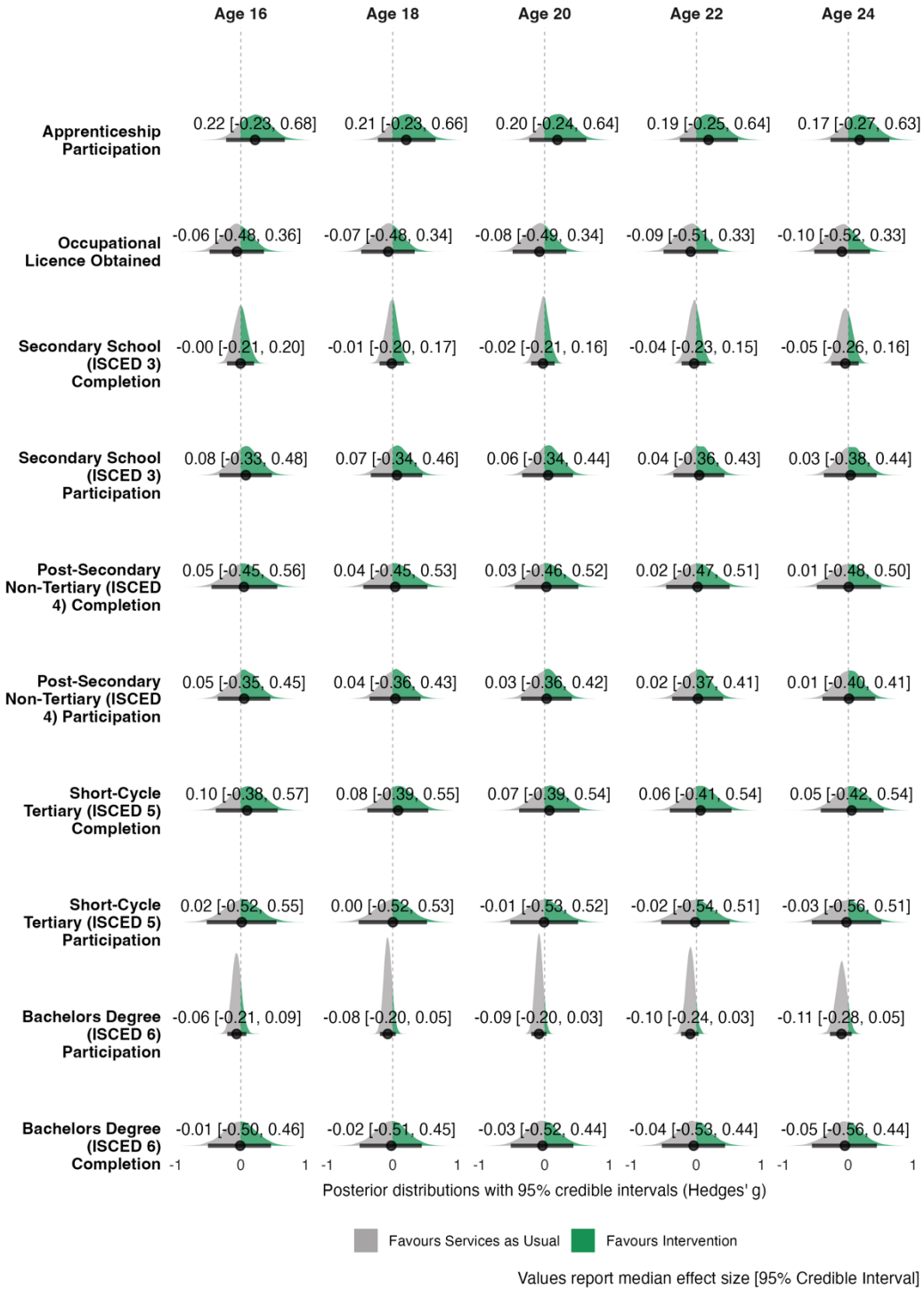


Figure 235 Impact of Job Specific Technical Skills (On-Job Training) on Education and Skills



Paid Temporary Work Experience

Figure 236 Impact of Paid Temporary Work Experience on Labour Force status

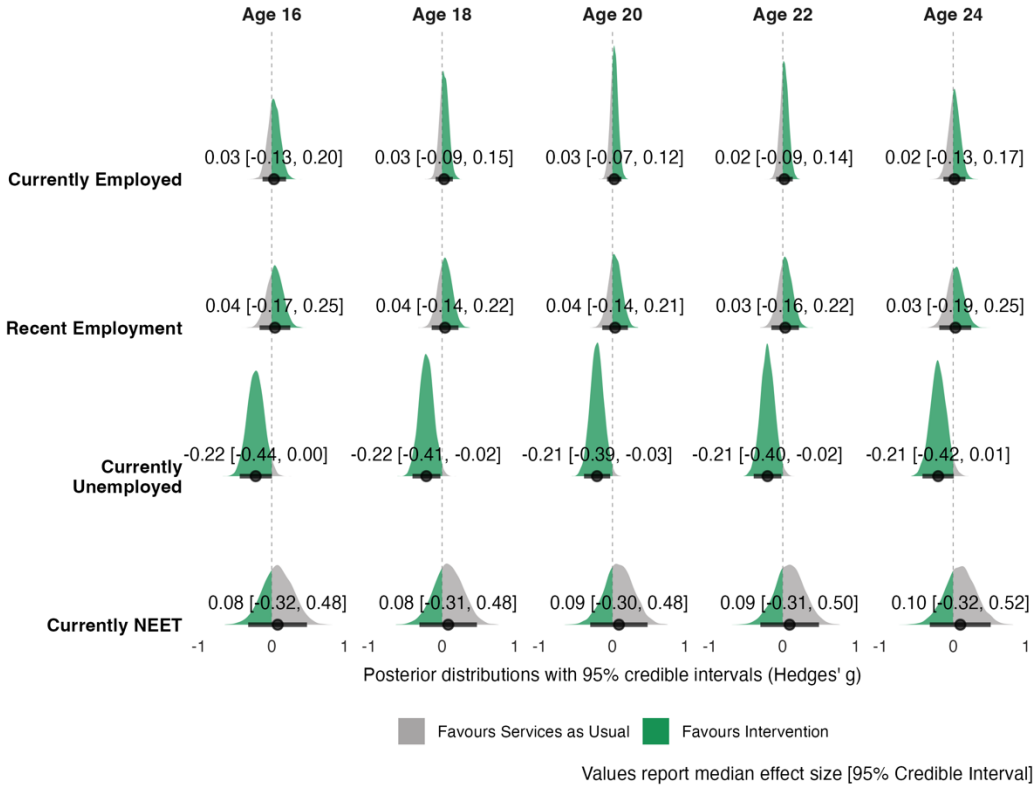


Figure 237 Impact of Paid Temporary Work Experience on Employment compensation

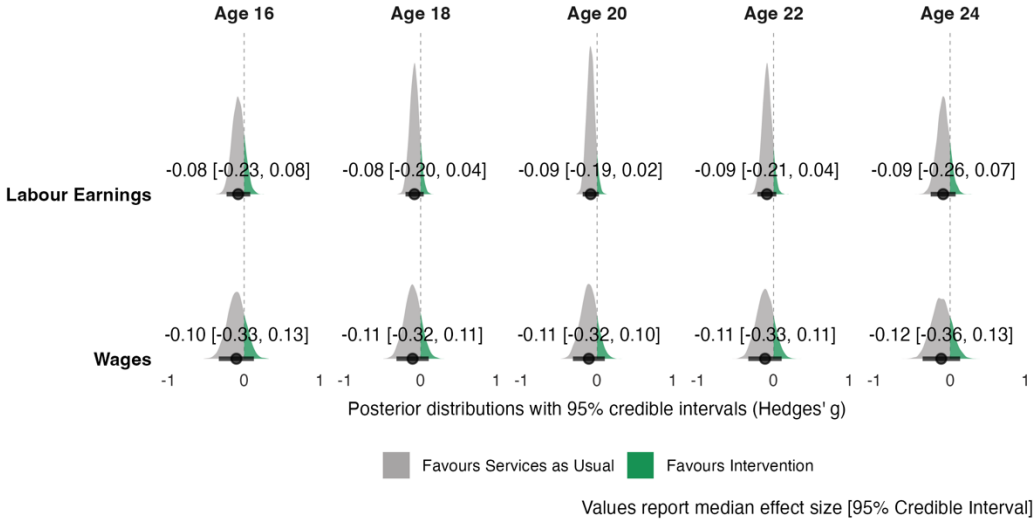


Figure 238 Impact of Paid Temporary Work Experience on Employment duration

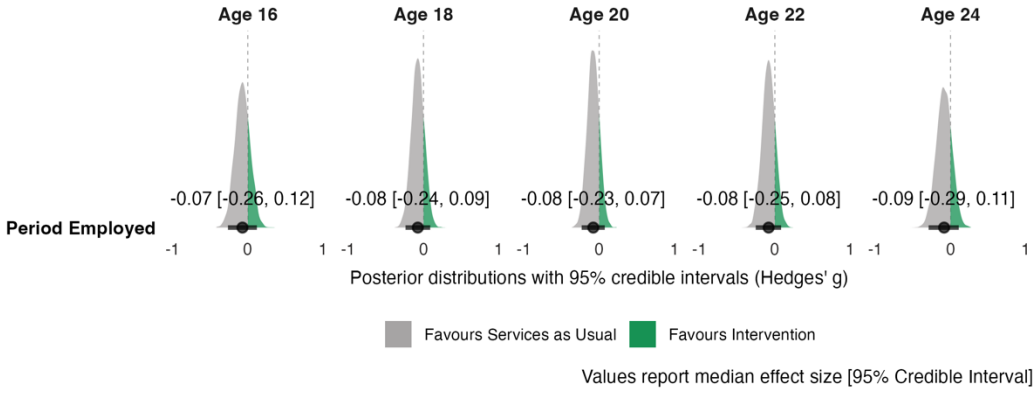
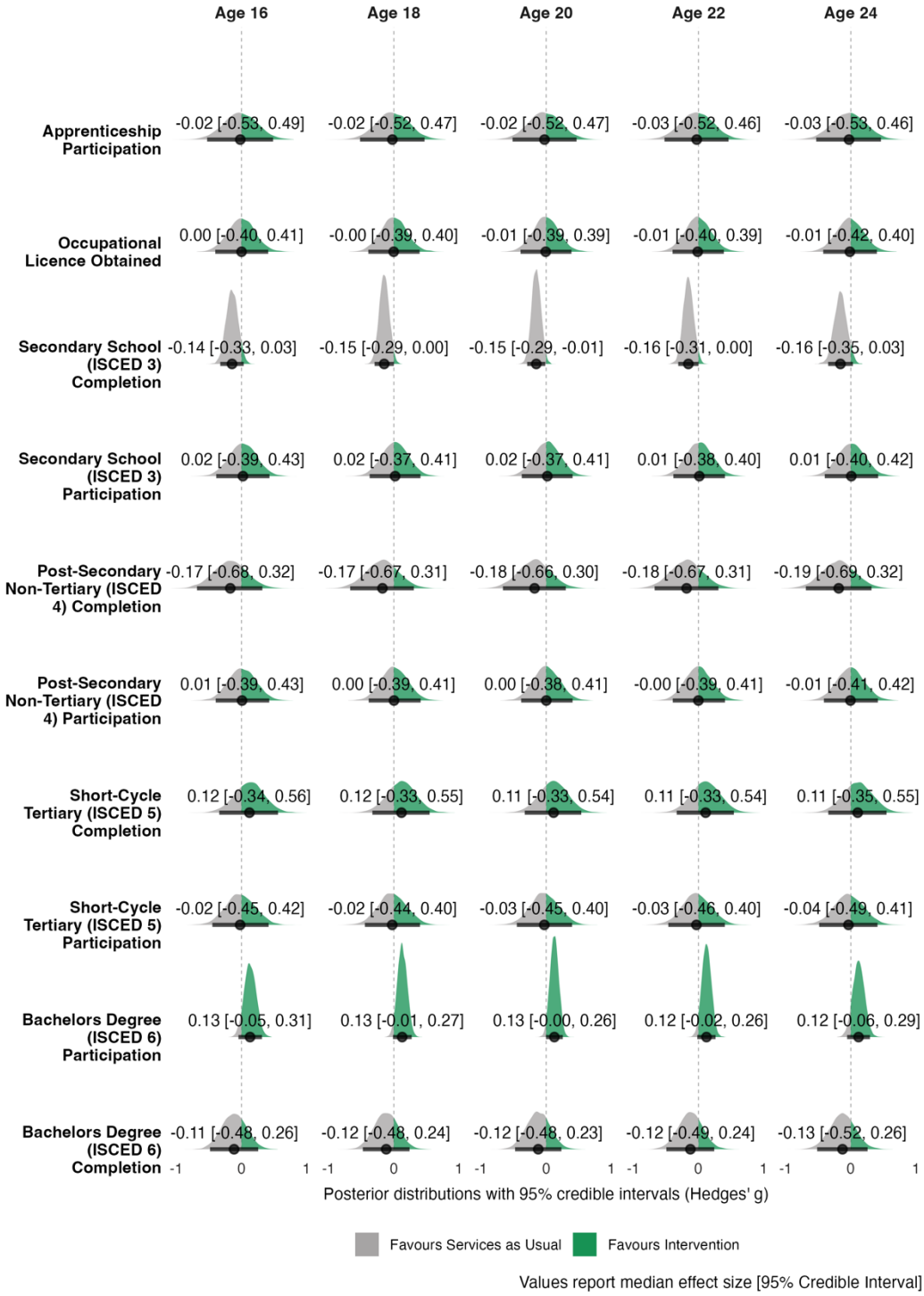


Figure 239 Impact of Paid Temporary Work Experience on Hours worked



Figure 240 Impact of Paid Temporary Work Experience on Education and Skills



Unpaid Temporary Work Experience

Figure 241 Impact of Unpaid Temporary Work Experience on Labour Force status

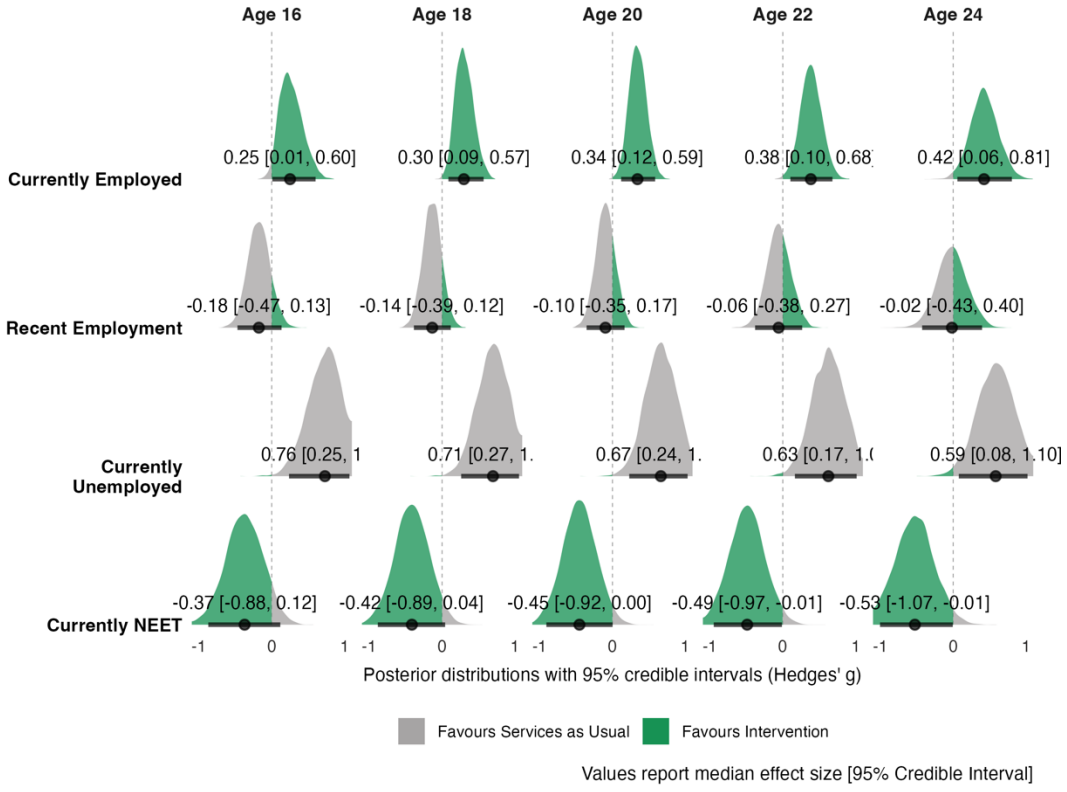


Figure 242 Impact of Unpaid Temporary Work Experience on Employment compensation

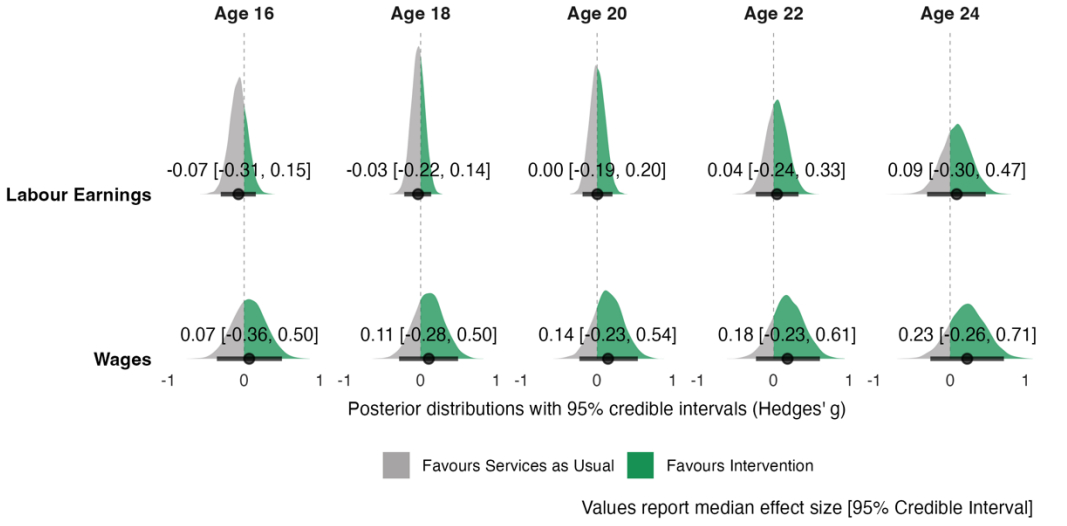


Figure 243 Impact of Unpaid Temporary Work Experience on Employment duration

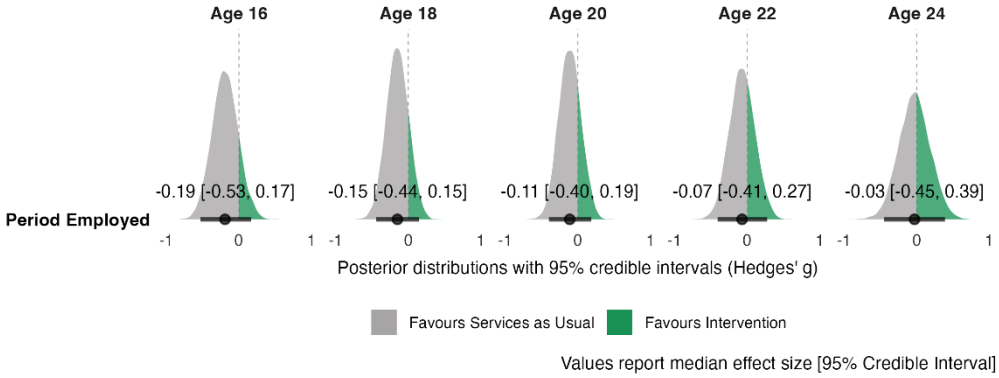


Figure 244 Impact of Unpaid Temporary Work Experience on Hours worked

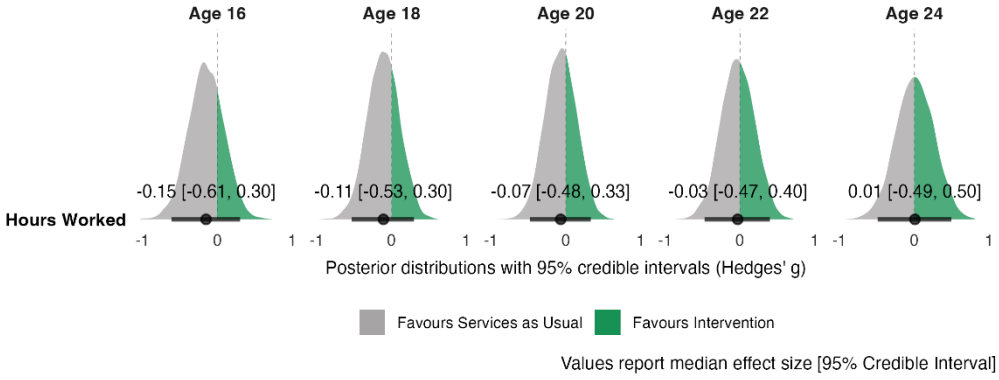
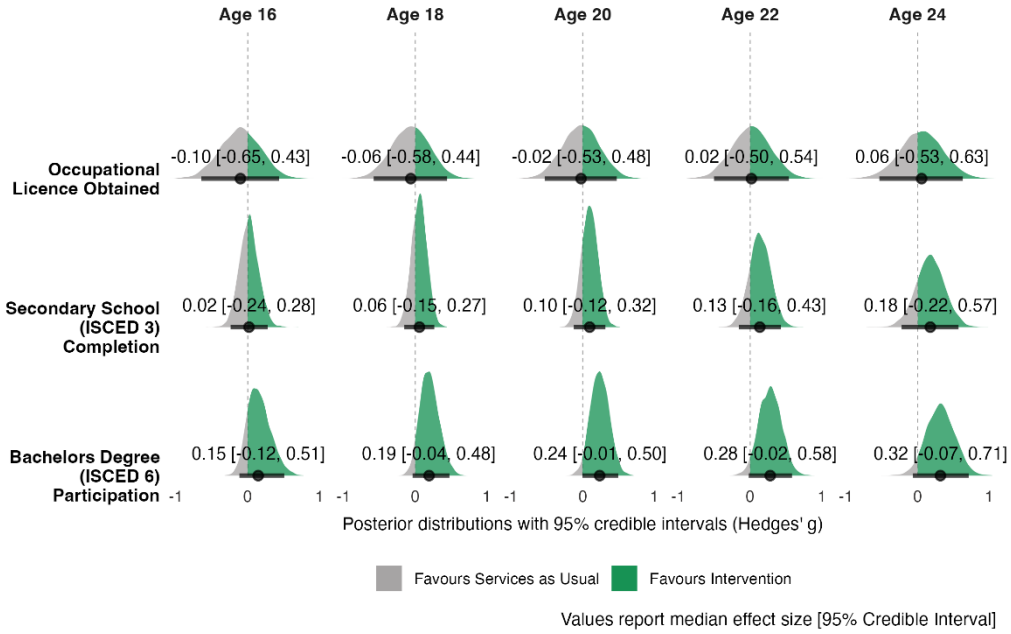


Figure 245 Impact of Unpaid Temporary Work Experience on Education and Skills



Wage Subsidies

Figure 246 Impact of Wage Subsidies on Labour Force status

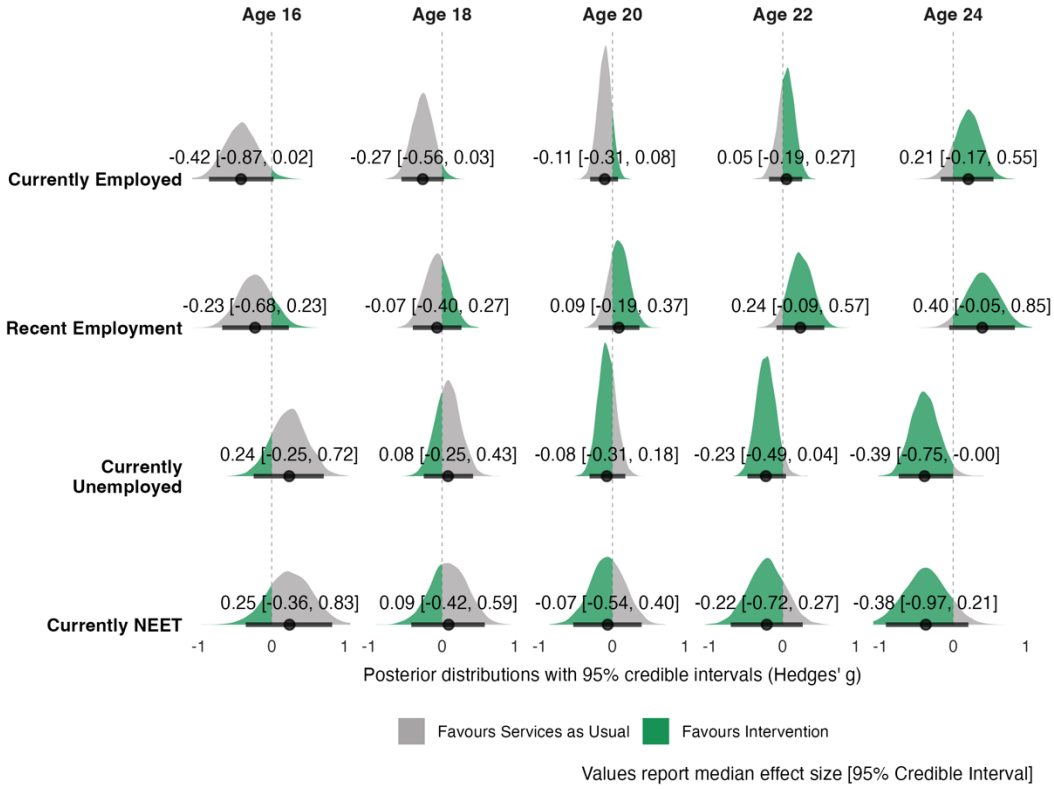


Figure 247 Impact of Wage Subsidies on Employment compensation

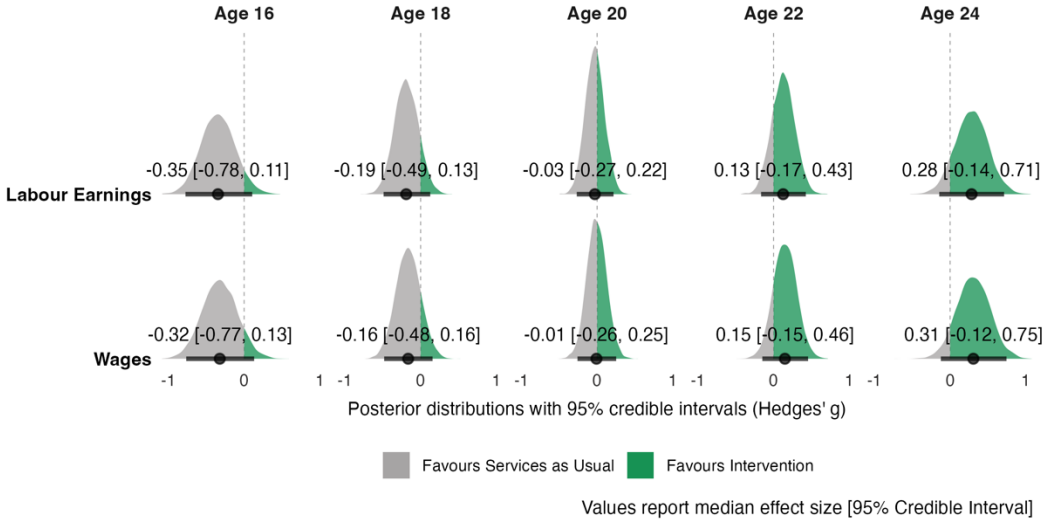


Figure 248 Impact of Wage Subsidies on Employment duration

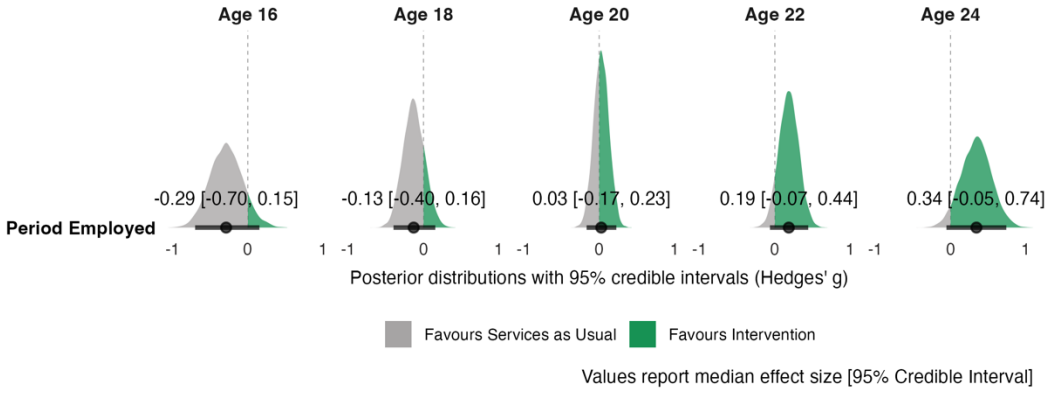


Figure 249 Impact of Wage Subsidies on Hours worked

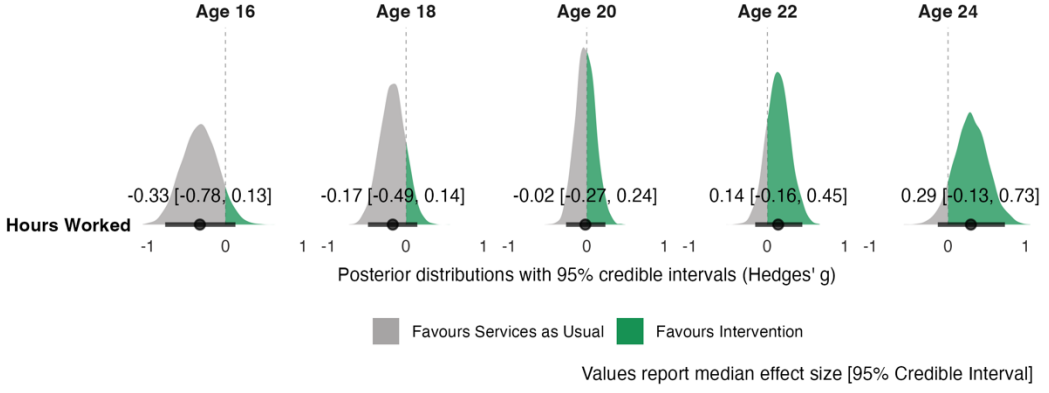
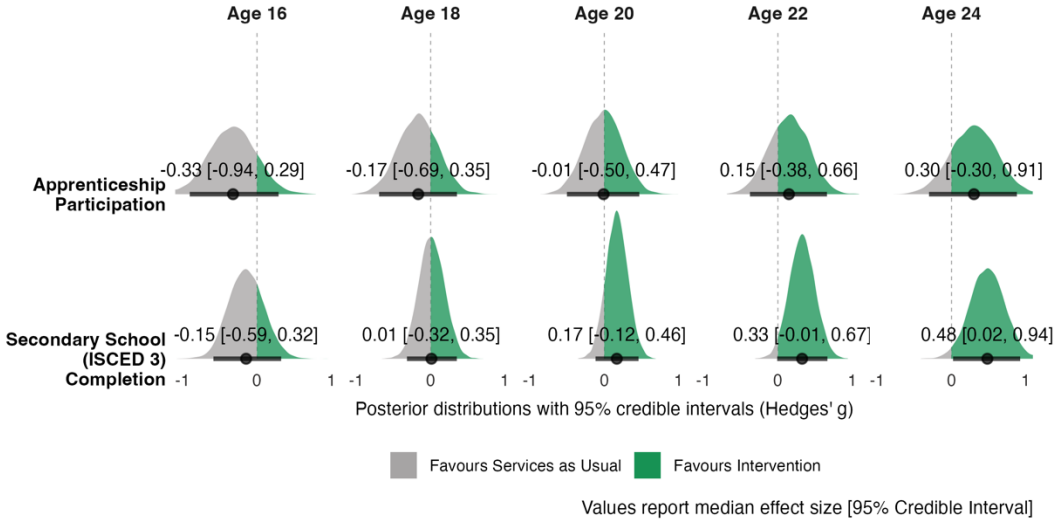


Figure 250 Impact of Wage Subsidies on Education and Skills



Public Works

Figure 251 Impact of Public Works on Labour Force status



Figure 252 Impact of Public Works on Employment compensation

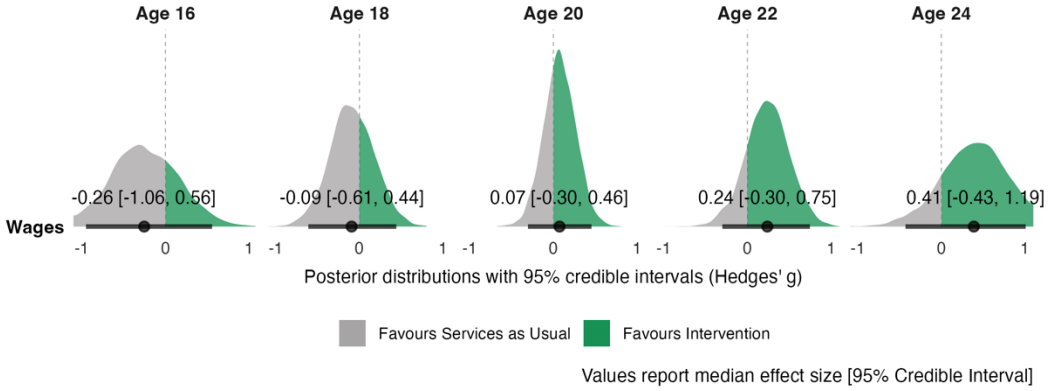


Figure 253 Impact of Public Works on Employment duration



About the research team

Youth Futures Foundation (YFF) commissioned a consortium consisting of the Centre for Evidence and Implementation (CEI), the Institute for Employment Studies (IES) and Monash University to conduct a review of the evidence on selected interventions to support youth employment, to inform the second edition of YFF's Youth Employment Toolkit.

Centre for Evidence and Implementation

The Centre for Evidence and Implementation (CEI) is a global, not-for-profit evidence intermediary dedicated to using the best evidence in practice and policy to improve the lives of children, families and communities facing adversity. Established in Australia in late 2015, CEI is a multi-disciplinary team across five offices in London, Oslo, Singapore, Melbourne and Sydney.

They work with their clients, including policymakers, governments, practitioners, programme providers, organisation leaders, philanthropists and funders in three key areas of work:

- Understand the evidence base
- Develop methods and processes to put the evidence into practice
- Trial, test and evaluate policies and programmes to drive more effective decisions and deliver better outcomes.

Data Matters, Monash University

Monash University, Australia's largest university, is ranked in the world's top 100 and is a member of the prestigious Group of Eight. It is widely recognised as one of the most international universities globally.

Data Matters is a research unit within the Department of Social Work. Our multidisciplinary team of social welfare researchers, quantitative analysts and engineers uses data-driven approaches to support evidence-informed social services. We bring together content knowledge and technical expertise across a range of social service contexts, including the use of administrative data. Our capabilities span experimental and quasi-experimental design, systematic reviews and meta-analysis, predictive modelling, and measuring implementation processes and outcomes.

We partner with government, philanthropic and research organisations striving to improve their decision making and service delivery.

Institute for Employment Studies

The Institute for Employment Studies (IES) is an independent, apolitical, international centre of research and consultancy in public employment policy and organisational human resource management. It works closely with employers, government departments, agencies, and professional and employee bodies.

For over 50 years IES has been a focus of knowledge and practical experience in employment and training policy, the operation of labour markets, and human resource planning and development.