Economic Effects of Gaining a Qualification in Later-life

– PRELIMINARY –

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Aims

- What is the long-term impact of obtaining a new qualification (on total earnings and wages)?
- Who tends to benefit?

Motivation: Gains in education for mature-age students

- Re-training and up-skilling
  - critical in light of automation and IT-skills-biased economy (Autor et al., 2008; Acemoglu and Autor, 2011)
  - facilitates career-change
- Expectation for re-training is across the whole income and age distribution
  - but existing literature focuses on younger ages (below age 25)
  - or on one type of setting such as in community colleges
- Total earnings versus wages

Idea and Contributions

- Focus on mature-age learners (age 25 or above)
- Earnings (both total and hourly)
- Returns to gaining different types of degrees and across the income distribution
- Machine Learning (ML) techniques applied to detailed and nationally representative data

Benefit 1 Construct a comparable counterfactual group

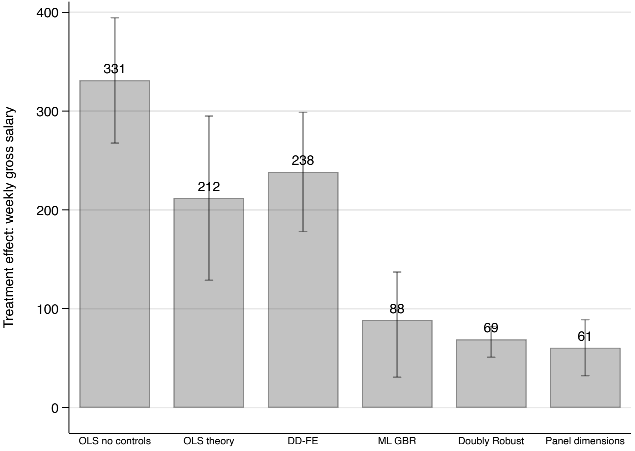
Benefit 2 A-theoretical approach to finding heterogeneous treatment effects

Why does ML Achieve those Benefits?

- Detect patterns in our (very) rich data e.g. important variables, functional forms and interactions
  - So what? Reduces mis-specification bias and can construct better counterfactuals
- Reduce information redundancy
  - So what? Reduces variance in estimators

Preview of Findings

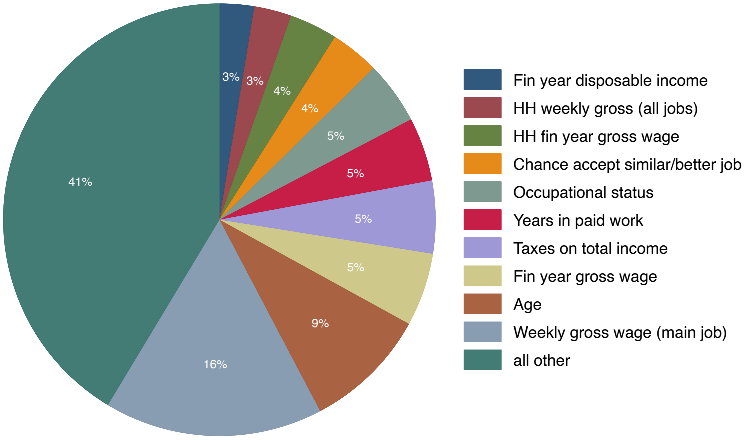
A ML-approach estimates a positive but smaller return to further education than traditional approaches



Notes: HILDA; sample size: 5,441 observations; 63,044 observations (Panel Dimension)

Preview of Findings

Effect sizes depend on starting income and age



DATA: HILDA

Several benefits to using HILDA data

- covers a long time-span (of nearly 2 decades, starting in 2001 and we use the wave 19 release)
- longitudinal data that details the year in which an individual started and completed further education
- wide range of background information on survey respondents

Sample

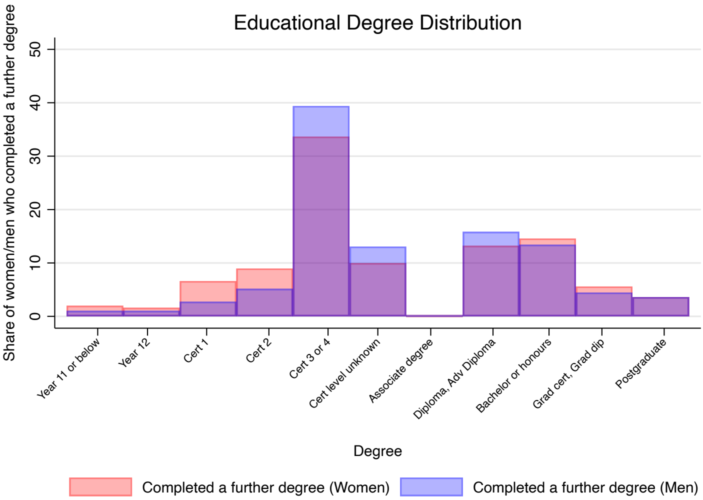
Our analysis sample includes:

- everyone who was 25 or above in 2001
- respondents not currently studying in 2001
- those observed in both 2001 and 2019 (and available information for Treatment and Outcome variables) and completed study by 2017
- Number of people in final sample: 5,441

Defining our Variables

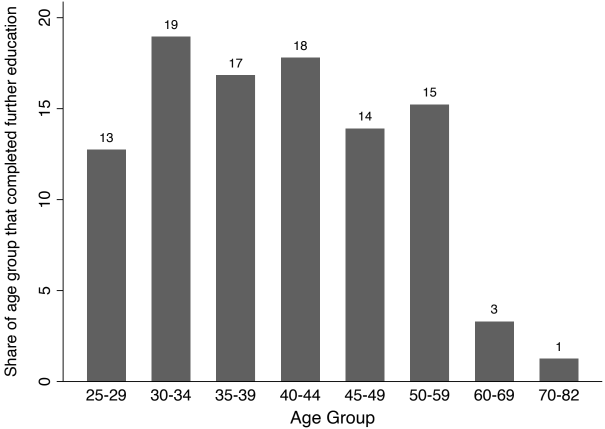
- Treatment indicator: obtaining an additional qualification between 2002 to 2017 (binary variable; 1,398 treated)
- Outcome variables: Earnings (total and hourly) in 2019
- Covariates or features: defined in 2001. Selected using a LASSO procedure.

Degree types by sex



Notes: HILDA; sample size: 5,441 observations

Degree completion by age (at 2001)



Notes: HILDA; sample size: 5,441 observations

Estimation goal and challenges

Aim: to estimate the causal returns to a new qualification

- The missing data problem

i	T	Y	Y(1)	Y(0)	Y(1) - Y(0)
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?

Notes: Made-up table

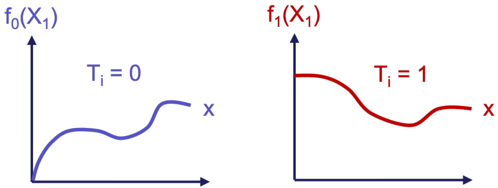
$$E[(Y_1)–(Y_0)] = E(Y_1)–E(Y_0) \neq E(Y_1|T = 1)–E(Y_0|T = 0) \quad (1)$$

How can ML help fill in the missing information?

- Standard ML predicts Y; alternatively, here we are interested in the causal parameter
- But no counterfactuals (no Individual Treatment Effects (ITEs))
- ML models can heavily penalise some variables that are weakly predictive of Y but strongly predictive of Treatment e.g. by shrinking their parameters
- Balance reducing this type of bias and increasing variance from including unnecessary variables in the model
- Adapt ML to fill in the missing data

T-learner

A potential solution



- Filling in the missing data blanks
  - two models: use 'treated' group to predict Y(1) and use 'control' group to predict Y(0)
  - for each person, we can plug their X's through the above two models to predict their outcomes when treated and when not treated
  - subtract difference of these two models to obtain estimated Individual Treatment Effects (ITEs)

Model selection

- Model classes: LASSO, Ridge, Gradient Boosting Regression (GBR)
  - LASSO and RIDGE are closely related to least squares but penalise complexity
  - GBR is a tree-based model: well-placed to pick up non-linearities
  - Tuning parameters are determined through cross-validation
  - GBR details gbr2

Model Selection

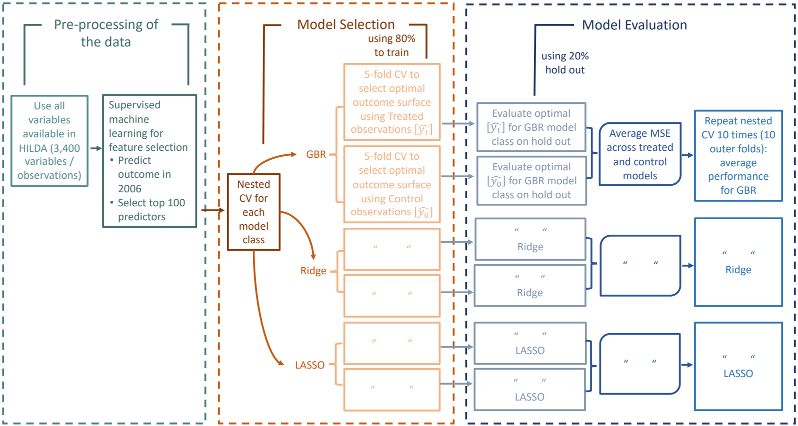


Table: Predictive Performance - Holdout Sample

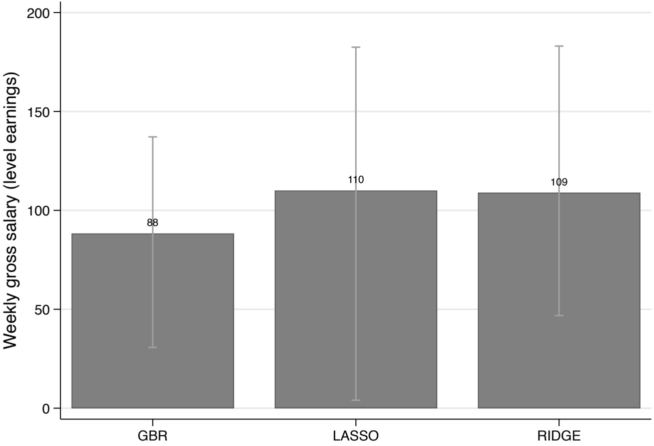
Model	Outcome surface	Out-of-Sample R-squared	R-squared SD
GBR	Treated	0.22	0.06
	Control	0.36	0.07
LASSO	Treated	0.15	0.09
	Control	0.32	0.05
Ridge	Treated	0.16	0.08
	Control	0.32	0.04

Notes: 5 fold CV performed on 80% train sample. All statistics presented in this table are based on the 20% holdout sample. Ten outer folds are used.

Inference

- Bootstrapping procedure
  - capture two sources of uncertainty: selecting the model and estimating the parameters
  - wider confidence intervals
- BS details explainer2

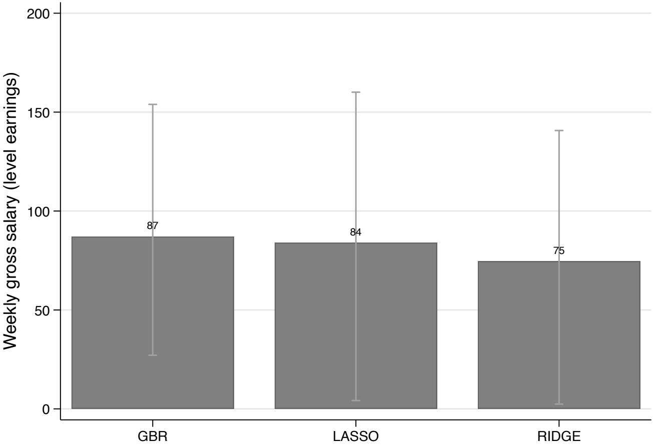
Results: Returns to Further Education



Notes: HILDA; sample size: 5,441 observations

GBR better Captures Non-linearities

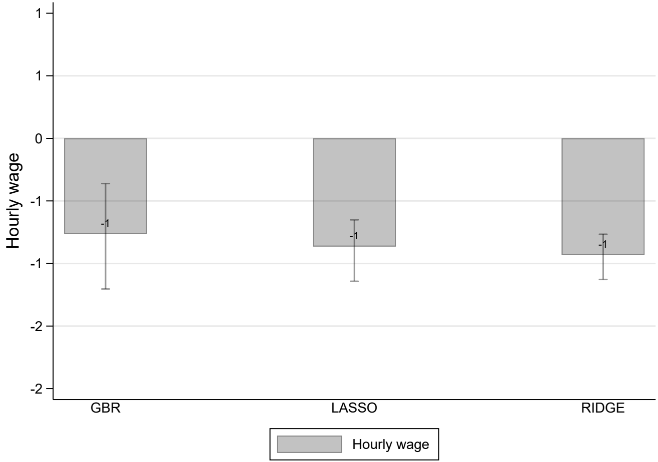
25 - 46-year-old (in 2001) sample



Notes: HILDA; sample size: 3,065 observations

Results: Wages

25 - 46-year-old (in 2001) sample



Improving on the T-learner

Doubly Robust

- Doubly Robust gives us two chances to get it right
- Previously, T-learner estimated the outcome of interest, given the treatment and the observable characteristics
- Here, we also estimate the probability of being treated, given the observable characteristics
- Combining above: robust to mis-specification of either model

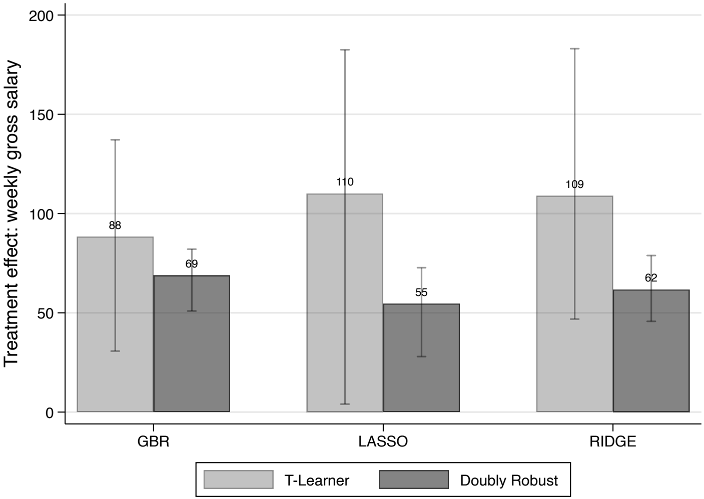
Doubly Robust

$$\hat{ATE} = \frac{1}{n}\sum_{i=1}^{n}[\frac{T_i(Y_i - \hat{\mu_1}(X_i))}{\hat{p}(X_i)} + \hat{\mu_1}(X_i)] - \frac{1}{n}\sum_{i=1}^{n}[\frac{(1-T_i)(Y_i - \hat{\mu_0}(X_i))}{1-\hat{p}(X_i)} + \hat{\mu_0}(X_i)]$$

- where:
  - $\hat{p}(X_i)$ is an estimation of the propensity score (using logistic regression)
  - $\hat{\mu_1}(X_i)$ is an estimation of E[Y|X,T=1] (using any ML model)
  - $\hat{\mu_0}(X_i)$ is an estimation of E[Y|X,T=0] (using any ML model)

Results

Doubly Robust

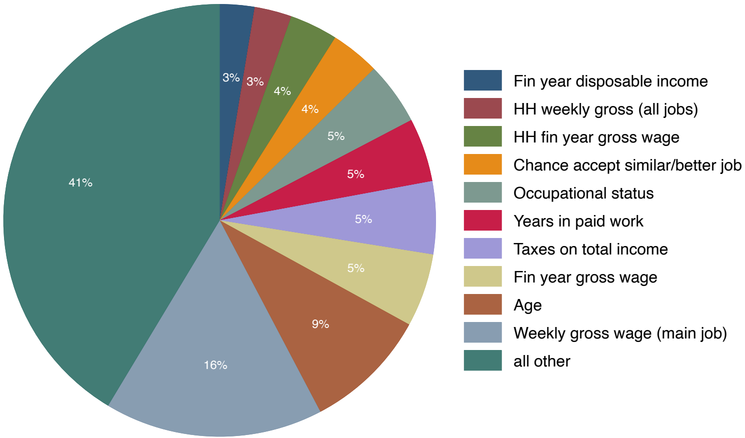


Notes: HILDA; sample size: 5,441 observations

- Is there a positive, long-run return to acquiring further education in later-life? ✓
- which groups were most affected?

Sub-group analysis

Effect sizes depend on starting income and age



Sub-group analysis

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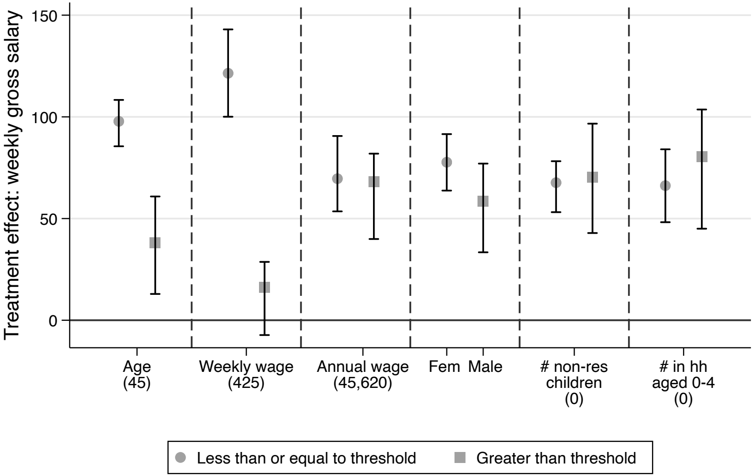


Note: Thresholds in parantheses

Summary of Other Results

- Acquiring an additional qualification may increase earnings through a number of potential mechanisms such as through getting a job, and switching occupations or industries
- Largest earnings gains are associated with acquiring an undergraduate degree or above and for technical subject areas
- Little evidence of well-being or mental health benefits

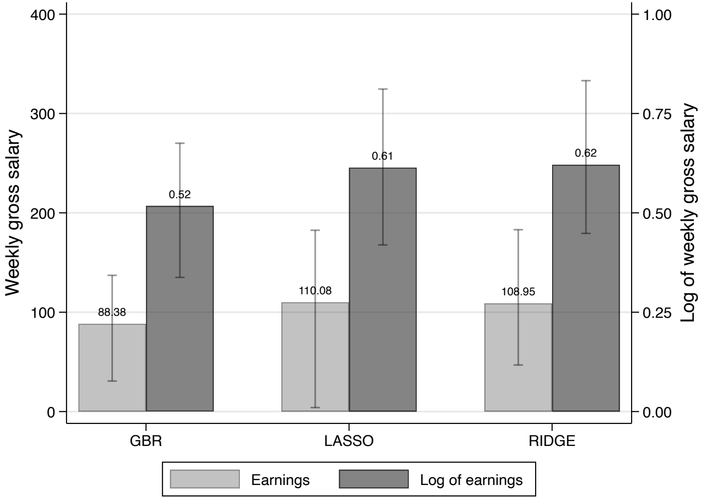
Conclusions

- Economic benefits to gaining an additional qualification in later-life
- An estimated gain of approximately $80 per week in gross earnings, which represents roughly 7 percent of the Average Weekly Gross Earning for the average worker in Australia
- Largest earnings gains are associated with younger learners and those with lower starting incomes

Appendix

Results: Returns to Further Education

Levels and Logs



Notes: HILDA; sample size: 5,441 observations

Sensitivity Analysis

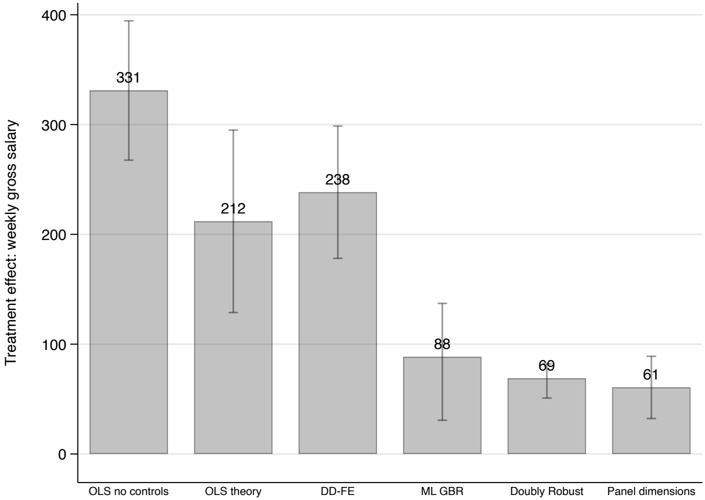
Defining features differently

We run sensitivity analysis on our approach

- Defining features differently: in year/s before study start
- Dealing with dynamic selection into further study
- Comparing the earnings of those who complete further study to the earnings of similar non-students who displayed the same paths (in earnings and other factors) as the student group before study began
  - Sample: 25 and above
  - Started studying in 2003 - 2017
  - In HILDA in two consecutive waves before study start
  - Could be in top-up sample or new joining household member (different from main analysis)
  - Started but did not complete are in the Control group
  - Control group are repeated: given a theoretical 'study-start' time stamp at every wave; standard errors adjusted

Sensitivity Analysis

Across all Methods



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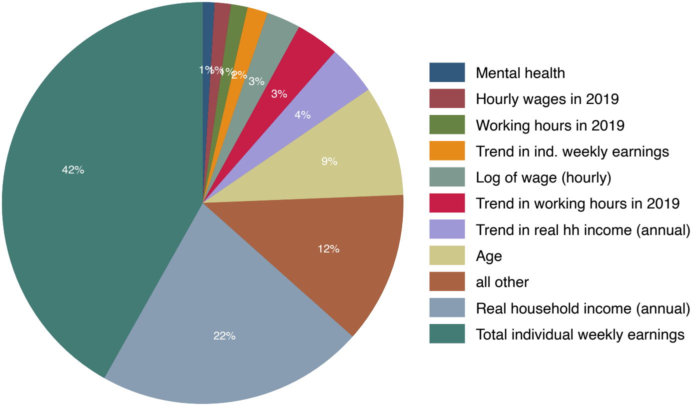
Sensitivity Analysis

Important Trend Predictors

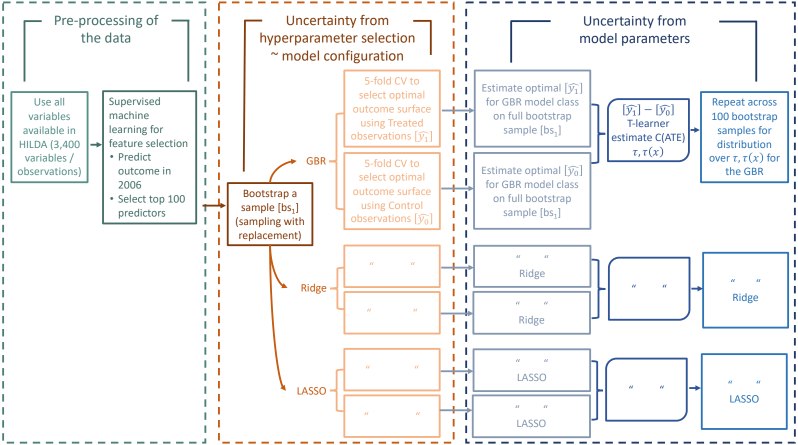


Notes: HILDA; sample size: 5,441 observations; 63,044 observations (Panel Dimension)

GBR details

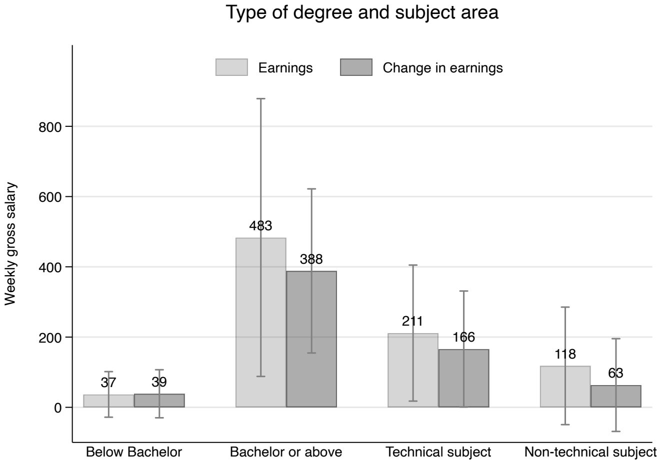
- In GBR, we sequentially fit small trees (i.e. you use the residuals from the previous tree to grow your next tree).
- Then we add a shrunken version of the new tree to the existing function and then update residuals and repeat
  - Number of trees (iterations)
  - Shrinkage – pace of learning
  - Number of splits (depth of tree) Back

Model Inference



◂ Back

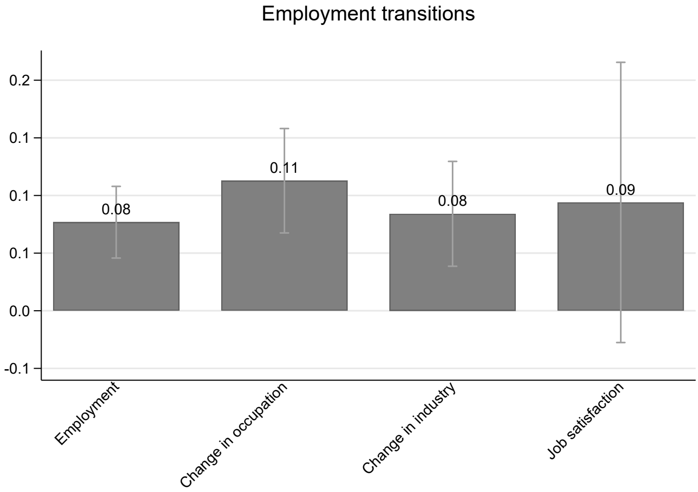
Higher-order degrees and technical subjects yield stronger effects



Notes: BB: 1,037; BA: 306; T: 681; NT: 662 *Technical*: STEM, Architecture, Ag and Env, Medicine, other health related studies and nursing, management and commerce and law. *Non — technical*: Education, Society and culture (includes economics!), Creative arts, and Food, hospitality and personal services

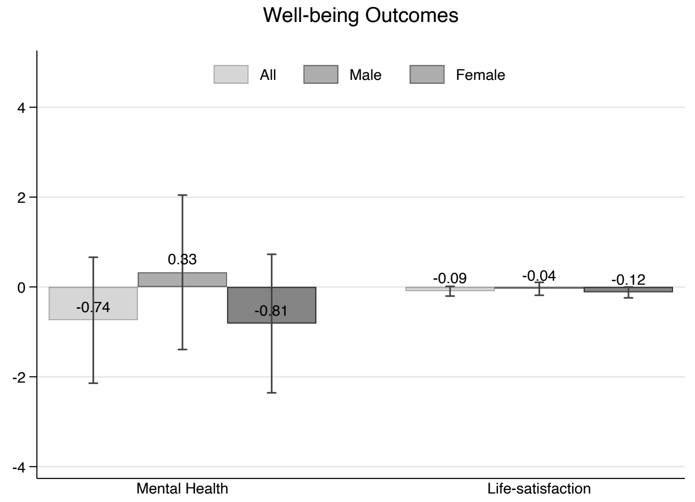
- Is there a positive, long-run return to acquiring further education in later-life? ✓
- Does the degree type and subject area matter? ✓
- Who was affected?
- Did it change long run labour market attachment?
- Any effects on mental health and wellbeing?

A larger workforce and a more mobile one



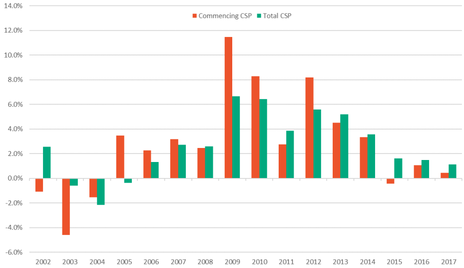
Notes: HILDA; ML model: LASSO

Small to no effects on wellbeing



Notes: HILDA; sample size: 5,441 observations; ML model: LASSO

Govt funding



Notes: DET, uCube