Replacing the Education Maintenance Allowance with the 16-19 Bursary in England: Effect on Education Participation

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The EMA was a cash transfer paid to 16-19 year olds from low-income households in the UK, conditional on post-compulsory education participation.

- Group 1: £30 per week if parental income < £20,817
- Group 2: £20 per week if £20,818 < parental income < £24,030
- Group 3: £10 per week if £24,031 < parental income < £30,810

Replaced with the 16-19 Bursary in September 2011 in England.

- Significant budget reduction from £560 million to £180 million.
- Schools now given autonomy over distribution amongst applications. Students encouraged to apply ‘if they need it’.
Aim of EMA was to increase participation amongst those from low-income backgrounds:

- High long-run ‘NEET’ rate in UK.
- Evidence of long run scarring from youth unemployment (Gregg & Tominey, 2004).
- Fits with broader agenda of addressing social mobility and access to H.E.

Evidence suggests EMA was broadly successful in raising participation:

- EMA pilot increased participation amongst eligible 16-19 year olds by 4.5 percentage points (Dearden et al, 2009).
Outline

- Difference-in-Differences 1: Comparing England with Scotland and Wales

- Difference-in-Differences 2: Comparing those above the EMA eligibility threshold with those below

- Structural Approach
EMA was preserved in both Scotland and Wales.

Ideal control group for D in D analysis?

Estimate overall effect on participation using LFS using the following model:

\[ Ed_{it} = \beta_0 + \beta_1 Eng + \beta_2 Post + \beta_3 Post * Eng + \gamma' X + t + \epsilon_{it} \]
Diff-in-Diff 1: Common Trends

Common trends assumption
Impact of policy

Post-16 outcomes

T-3  T-2  T-1  T  T+1  T+2

Time

Comparison group (never eligible for EMA)
Affected group (formerly EMA eligible)
Diff-in-Diff 1: Common Trends

Proportion of 16 YO's in FT Ed

- Rest of UK
- England

Years: 2005/06 to 2010/11
Diff-in-Diff Estimate of Effect on Education Participation

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Treat</td>
<td>0.76***</td>
<td>-0.02***</td>
<td>-1.17***</td>
<td>-1.56***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.11)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Eng</td>
<td>5.60***</td>
<td>5.71***</td>
<td>2.27***</td>
<td>2.82***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.12)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Post</td>
<td>2.71***</td>
<td>3.27***</td>
<td>2.63***</td>
<td>3.27***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.03)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>$R^2$/Pseudo</td>
<td>0.005</td>
<td>0.005</td>
<td>0.14</td>
<td>0.11</td>
</tr>
<tr>
<td>$R^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>10,212</td>
<td>10,212</td>
<td>9,859</td>
<td>9,859</td>
</tr>
</tbody>
</table>

All data are from the LFS between 2003 and 2012. Controls for ethnicity, gender and high GCSE’s are included as well as quarterly dummies. * indicates significant at 10%, ** = significant at 5% and *** = significant at 1%. Standard errors clustered at country level are given in the parentheses. Observations are weighted using the LFS population survey weights.
Diff-in-Diff 1: Drawbacks

- LFS data limited for background characteristics.
  - Poor prediction of parental income, meaning we can’t estimate EMA eligibility well.
  - Hence look at overall effect here only.

- Concern about common trends.

- And concerned about tuition fee changes in England.
Those slightly above the income eligibility should in theory be unaffected by the policy change.

Ideal control group for D in D analysis?

Estimate overall effect on participation using administrative English datasets (NPD, ILR, Pupil Census), using the following model:

$$Ed_{ist} = \beta_0 + \beta_1 \text{Group1} + \beta_2 \text{Group2} + \beta_3 \text{Group3} + \beta_4 \text{Group5} + \beta_5 \text{Post} + \beta_6 \text{Post} \times \text{Group1} + \beta_7 \text{Post} \times \text{Group2} + \beta_8 \text{Post} \times \text{Group3} + \beta_9 \text{Post} \times \text{Group5} + \gamma'X + t + u_s + \epsilon_{ist}$$

Can investigate Year 12 and 13 Participation and Level 2 and 3 attainment.
Diff-in-Diff 2: Common Trends

- **Y12 FT Participation Males**
- **Groups:**
  - Group 1
  - Group 2
  - Group 3
  - Group 4
  - Group 5

Years:
- 2004/05
- 2005/06
- 2006/07
- 2007/08
- 2008/09
- 2009/10
- 2010/11
## Diff-in-Diff 2: Results

<table>
<thead>
<tr>
<th></th>
<th>Impact on lowest-income pupils (who would have been eligible for maximum EMA support)</th>
<th>Impact across all pupils who would have been eligible for any EMA support</th>
<th>Impact across cohort as a whole</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Y12 FT participation</strong></td>
<td>-1.65 ppts</td>
<td>-1.07 ppts</td>
<td>-0.65 ppts (83.9%)</td>
</tr>
<tr>
<td><strong>Y13 FT participation</strong></td>
<td>-1.75 ppts</td>
<td>-1.50 ppts</td>
<td>-0.88 ppts (69.7%)</td>
</tr>
<tr>
<td><strong>L2 by 18 attainment</strong></td>
<td>-1.83 ppts</td>
<td>-1.52 ppts</td>
<td>-0.90 ppts (82.8%)</td>
</tr>
<tr>
<td><strong>L3 by 18 attainment</strong></td>
<td>-0.09 ppts</td>
<td>-0.05 ppts</td>
<td>-0.03 ppts (48.0%)</td>
</tr>
</tbody>
</table>
Diff-in-Diff 2: Drawbacks

- Difficult to identify those just above the threshold.

- Even if people are correctly identified as being above the old threshold, they might still receive the Bursary (so may not be completely unaffected).

- Common trends seems ok... but changes to tuition fees might still be a problem.

- Potential concern over spillover (through composition effects) - more relevant for attainment.
Structural Approach: The Model

- Discrete Choice Dynamic Programming.

- Model of choices: individuals choose between three discrete choices (Work, School and Home) every year.

- Each is associated with a utility accrued in that period.

- Model is ‘dynamic’ in that current period choices affect future utility returns.

- Individuals know expected value of the future and make choices to maximise lifetime utility.
In each of the 3 states receive the following utility in that period (where $X_t$ & $Y_t$ are accumulated experience and schooling at the start of period $t$):

$$W_t = \exp(\beta_0 + \beta_1 X_t + \beta_2 Y_t + \epsilon_{1t})$$

$$S_t = s - tuition - rc + EMA + CB + \epsilon_{2t}$$

$$H_t = h + Benefits + \epsilon_{3t}$$

Estimated using the BHPS.

I use cohorts that are post-EMA, pre-recession (due to concerns that the recession affected structural parameters). So from 2004 to 2008.
## Structural Approach: Model Fit

<table>
<thead>
<tr>
<th>Overall</th>
<th>Work</th>
<th>School</th>
<th>Home</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 1</td>
<td>12.5</td>
<td>82.6</td>
<td>4.9</td>
</tr>
<tr>
<td></td>
<td>(9.5)</td>
<td>(84.9)</td>
<td>(5.7)</td>
</tr>
<tr>
<td>Period 2</td>
<td>20.1</td>
<td>72.7</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>(21.0)</td>
<td>(71.5)</td>
<td>(7.8)</td>
</tr>
<tr>
<td>Period 3</td>
<td>41.2</td>
<td>45.8</td>
<td>13.0</td>
</tr>
<tr>
<td></td>
<td>(41.4)</td>
<td>(47.0)</td>
<td>(11.6)</td>
</tr>
</tbody>
</table>

True values from the BHPS dataset are given in the parentheses.
### Structural Approach: Policy Simulations

<table>
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<th></th>
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</thead>
<tbody>
<tr>
<td><strong>Eligible</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work</td>
<td>10.4</td>
<td>13.9</td>
<td>12.8</td>
<td>8.4</td>
</tr>
<tr>
<td>School</td>
<td>83.9</td>
<td>79.5</td>
<td>80.8</td>
<td>85.9</td>
</tr>
<tr>
<td>Home</td>
<td>5.6</td>
<td>6.6</td>
<td>6.3</td>
<td>5.5</td>
</tr>
<tr>
<td><strong>Ineligible</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work</td>
<td>8.8</td>
<td>8.8</td>
<td>8.8</td>
<td>8.3</td>
</tr>
<tr>
<td>School</td>
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<tr>
<td>Home</td>
<td>2.3</td>
<td>2.3</td>
<td>2.3</td>
<td>3.3</td>
</tr>
<tr>
<td><strong>Overall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work</td>
<td>9.8</td>
<td>11.9</td>
<td>11.2</td>
<td>8.4</td>
</tr>
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<td>School</td>
<td>85.9</td>
<td>83.2</td>
<td>84.0</td>
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<tr>
<td>Home</td>
<td>4.3</td>
<td>4.9</td>
<td>4.7</td>
<td>4.7</td>
</tr>
</tbody>
</table>
Structural Approach: Drawbacks

- Question marks about inference using a pre-reform cohort only.

- Difficult to get meaningful confidence intervals.

- EMA eligibility difficult to estimate in the BHPS due to poor parental income measures.
Presented 3 methods estimating the effect of policy replacing the EMA with the 16-19 Bursary in England.

Estimated (overall) effect of -1.6pp, -0.65pp and -1.9pp for the 3 methods.

Imply 2-3 pp drop amongst those eligible for the full EMA.

Structural model can be extremely revealing for policy - even if the point estimate is not perfect.

Combination of structural and reduced-form estimates is ideal: i.e constrain the model to replicate results from policy experiments.

External validation also important.