Strains and Gains
Estimating a First Year University Student Online Engagement Effect
Stata Extended Regression Model (ERM) Framework

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Enabling Engagement: Contexts and Questions

This paper addresses three main issues:

• *Do reported levels of online engagement of First Year enrolments predict the Numerical Grades Awarded?*

• *Can an ERM “wash out” the endogenous effects of covariate bias, sample selection in estimation of an “engagement effect?*

• *What are the strengths and weaknesses of the Extended Regression Modelling (ERM) framework in evaluation research for HE innovation?*
Policy and Performance
The Rise of “Distributed Learning”

Diagram:
- Equity Targets: SES, Disability, Region
- Demand-Driven Policy
- Explosion of Student Numbers
- Rise of "Distributed" / eLearning Strategies
- Diversity of Student Intake
- Local University Conditions
- Decline in per Student Funding
Diversity and Delivery: the CDU Context

Charles Darwin University Student Profile*


The Externalisation of Course Delivery

* All Common Unit Enrolments (n=21, 615)
Flexible Learning: the CDU Response: 2002-2016

- All units and courses now available online (offered to Open University Australia, plus 3 MOOCs)

- Learnline Management System and Virtual classroom (Collaborate) widely available in both attendance modes (with mobile access)

- Online portal for full student services plus social media platform (with ShareStream for video)
The Research Questions: Online Activity and Student Success

I. Do increased levels of online activity exert a uniform and positive effect on grade levels, after “confounding” variables (student background and admission entry categories) are controlled?

II. Does an effect (sign, size, significance) also depend on learning context- External Mode, Part-time Status or Unit Type (Common Unit or Core Unit)?

III. How might we infer a causal effect for exposure to and participation in online participation on student grades?
Estimating Online Effect: From Regression to Causal Inference

The size and significance of online activity effect is represented by the red arrow.

Student Profile
- Demographics
- Language
- “First in family”
- Basis of Admiss’n

Study Situation
- Full/Part/Time
- Mode of study
- Medium/Delivery
- Assessment type

Online Activity (Learnline)
- Accesses
- Minutes Online
- Clicks
- Submissions/Posts

Outcomes
- Retention in Unit
- Grade Awarded
- Progression

Can we reconfigure this path model to emulate an experimental (RCT) model?
### The Sample: Outcome, “Treatment” & Confounders

<table>
<thead>
<tr>
<th>Variable</th>
<th>S2 2017</th>
<th></th>
<th>S1 2018</th>
<th></th>
<th>Combined</th>
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<tr>
<td></td>
<td>Obs</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Obs</td>
<td>Mean</td>
<td>Std. Dev.</td>
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<td><strong>Outcome</strong></td>
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<td></td>
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<tr>
<td>Numerical Grade (2-7)</td>
<td>2,398</td>
<td>4.52</td>
<td>1.34</td>
<td>2,581</td>
<td>4.66</td>
<td>1.42</td>
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<td><strong>Learnline Engagement</strong></td>
<td></td>
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</tr>
<tr>
<td>Number of Unit access</td>
<td>2,398</td>
<td>60.00</td>
<td>41.43</td>
<td>2,581</td>
<td>73.29</td>
<td>47.03</td>
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<tr>
<td>TotalClicks/Interactions</td>
<td>2,398</td>
<td>398.68</td>
<td>302.22</td>
<td>2,581</td>
<td>528.05</td>
<td>389.71</td>
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<tr>
<td>Total minutes online</td>
<td>2,398</td>
<td>1286.29</td>
<td>1193.59</td>
<td>2,581</td>
<td>1698.95</td>
<td>1421.66</td>
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<td><strong>Learning Situation</strong></td>
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<td>Common Unit</td>
<td>2,398</td>
<td>0.48</td>
<td>0.50</td>
<td>2,581</td>
<td>49.32%</td>
<td>50.01%</td>
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<td>49.09%</td>
<td>2,581</td>
<td>65.05%</td>
<td>47.69%</td>
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<tr>
<td>Part-time Status</td>
<td>2,398</td>
<td>31.65%</td>
<td>46.52%</td>
<td>2,581</td>
<td>28.86%</td>
<td>45.32%</td>
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<td><strong>Student Demographics</strong></td>
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<tr>
<td>Male</td>
<td>2,397</td>
<td>38.55%</td>
<td>48.68%</td>
<td>2,581</td>
<td>26.39%</td>
<td>44.08%</td>
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<td>NESB</td>
<td>2,398</td>
<td>31.40%</td>
<td>46.42%</td>
<td>2,581</td>
<td>23.01%</td>
<td>42.10%</td>
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<td>Indigenous_Status</td>
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<td>5.67%</td>
<td>23.13%</td>
<td>2,581</td>
<td>6.47%</td>
<td>24.60%</td>
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<tr>
<td>Age in Years</td>
<td>2,398</td>
<td>28.05%</td>
<td>9.63</td>
<td>2,581</td>
<td>28.66%</td>
<td>9.52</td>
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<tr>
<td>TER_Present</td>
<td>2,398</td>
<td>18.27%</td>
<td>38.65%</td>
<td>2,581</td>
<td>10.23%</td>
<td>30.31%</td>
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</table>
Regression Results: Linear and Non-Linear

Fig. 5 Marginsplot Comparisons of Engagement Effect in Univariate and Multivariate Regressions

Linear Regression

- Multivariate Model: $R^2 = 25.7\%$
- Univariate Model: $R^2 = 16.4\%$

Cubic Regression

- Multivariate Model: $R^2 = 37.3\%$
- Univariate Model: $R^2 = 28.7\%$
Developing an Extended Regression Model*

The term “endogenous” is used most frequently to encompass the distorting confounding or “non-ignorable” effects of:

• **endogenous covariates**: where a background variable which may have a confounding effect on response to a treatment. These need to be included in the estimation (cf Analysis of Covariance).

• **sample selection**: where the participants in such a trial were overwhelmingly drawn from a non-representative group of the target population (e.g. in the weightloss example, from a group that had a history of chronic eating disorders);

• **treatment assignment**: where those who were assigned to the treatment group rather than the ‘control’ or non-treatment group were unbalanced across one or more critical dimensions (e.g. on ethnicity, age or gender).

*Users are referred to similar ERM model for estimating an intervention effect for a “Fictional University” in Chuck Huber’s presentation at this Conference, available at [https://tinyurl.com/2019CausalInference](https://tinyurl.com/2019CausalInference)*
Estimating Online Effect: A Generic Framework

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Building an ERM of Online Engagement Effect

These three sources of endogeneity will be addressed within an Extended Regression Modelling framework. Each is followed by a research question of practical interest:

• **Endogenous covariates** In this model two covariates, Part-time Status (defined as an EFTSL score below .375 or one or two units associated with each enrolment per semester) and External Mode of Attendance, are identified as endogenous.

• **Sample Selection Bias** The status of the lowest scoring group (FNS/DNS) in the scale of Grade Awarded outcomes raises an important issue of endogeneity that precedes that of treatment assignment or levels of engagement. These were treated by a Heckman-type selection model (similar to Chuck Huber’s use of the same approach for missing data).

• **Endogeneity in Assignment to Treatment** - in a self-selection design, recognises that:
  
  i. more motivated and committed students will be more likely to have higher activity scores than others, even after adjustment self select to a level of online engagement;

  ii. conversely, lower ability students who are more at risk of attrition or failure may be more likely to rely on the resources and support offered by Blackboard and other systems.
**Sourcing Endogeneity: Covariate, Engagement and Sample Selection**

<table>
<thead>
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<tbody>
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<td>corr(e.graded_3plus,e.gradescale2)</td>
<td>0.312</td>
<td>0.088</td>
<td>3.570</td>
<td>0.000</td>
<td>0.132</td>
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<tr>
<td>corr(e.engage_strat5a,e.gradescale2)</td>
<td>0.574</td>
<td>0.076</td>
<td>7.560</td>
<td>0.000</td>
<td>0.407</td>
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<tr>
<td>corr(e.Part_time,e.gradescale2)</td>
<td>0.544</td>
<td>0.149</td>
<td>3.650</td>
<td>0.000</td>
<td>0.193</td>
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<td>corr(e.External_Mode,e.gradescale2)</td>
<td>0.058</td>
<td>0.015</td>
<td>3.790</td>
<td>0.000</td>
<td>0.028</td>
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<td>corr(e.engage_strat5a,e.graded_3plus)</td>
<td>0.743</td>
<td>0.018</td>
<td>41.990</td>
<td>0.000</td>
<td>0.706</td>
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<tr>
<td>corr(e.Part_time,e.graded_3plus)</td>
<td>-0.038</td>
<td>0.025</td>
<td>-1.510</td>
<td>0.131</td>
<td>-0.088</td>
</tr>
<tr>
<td>corr(e.External_Mode,e.graded_3plus)</td>
<td>-0.076</td>
<td>0.025</td>
<td>-3.000</td>
<td>0.003</td>
<td>-0.125</td>
</tr>
<tr>
<td>corr(e.Part_time,e.engage_strat5a)</td>
<td>-0.007</td>
<td>0.018</td>
<td>-0.380</td>
<td>0.705</td>
<td>-0.043</td>
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<tr>
<td>corr(e.External_Mode,e.engage_strat5a)</td>
<td>0.048</td>
<td>0.018</td>
<td>2.680</td>
<td>0.007</td>
<td>0.013</td>
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<tr>
<td>corr(e.External_Mode,e.Part_time)</td>
<td>0.119</td>
<td>0.016</td>
<td>7.350</td>
<td>0.000</td>
<td>0.087</td>
</tr>
</tbody>
</table>

* "engage_strat5a" is multivalued “treatment” variable defined as a five-level grouping of the means of three Learnline activity zscores.
  “gradescale2” and “graded_3plus” are the dependent variables for the full sample (includes the DNS/FNS grades) and the “selected” sample (excludes the DNS/FNS) respectively.
Potential Grades at Five Levels of Online Engagement*

n=4,978 observations (standard error adjusted for 3,192 clusters)

*Blackboard Learnline Activity scores – Learnline is a compulsory learning system for all enrolments
Potential vs Observed Outcomes

Quantile-Quantile Plot
Potential Gains: Indigenous Enrolments by Attendance Status

[Bar chart showing mean grade difference potential minus observed for Non-Indigenous and Indigenous students, differentiated by internal & full-time, external & full-time, internal & part-time, and external & part-time attendance status.]
"Strains and Gains": a Summary

**Strains**

- Causal attribution requires more sensitive discriminators for exposure vs participation when “treatment” (level of online engagement) is either compulsory or universal.
- Multivalued treatment scoring may complicate estimates of marginals and contrasts.
- Lack of multiway vce (cluster) restricts levels of “nested” effects estimation.

**Gains**

- ERM Release 15 provides consistent estimators in a complex Higher Education valuation research.
- Combined auxiliary equations (with eregress) can reproduce the non-linear fit of an OLS cubic expansion.
- Positive treatment effects of online engagement are unevenly distributed, with highest potential “gains” at the lower end of observed grade distribution.