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Title	Longitudinal analysis of students' learning gains in Higher Education across two UK institutions
Session	Merits and challenges of measuring learning gains for learning, teaching and assessment: Lived experiences of 78,531 students at 16 universities. (Rogaten)
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Longitudinal analysis of students' learning gains in Higher Education across two UK institutions

Introduction

What students gain through going to University has become a subject of increasing debate. This debate has been driven in part by the increasing requirement of governments for Higher Education Institutes (HEI) to be accountable to their funders. In part, universities are keen to align their missions to the widening participation agenda, and aim to be recognised for the 'high level of benefit' that universities bring to their students. Most definitions of learning gain utilise the metaphor of 'distance travelled'. The starting point on this journey is often taken when students enter university, whilst the amount of knowledge and understanding gained refers to the distance travelled on a particular journey. The acquisition of skills and development of particular attributes could be considered as separate but related journeys that students embark on. The definition of learning gain adopted by HEFCE is an attempt to measure the improvement in knowledge, skills, work-readiness and personal development made by students during their time spent in higher education.

Although learning gain as a concept is relatively easy to define, its measurement however is problematic and contentious McGrath et al (2015). The essence of the learning gains measurement debate is that the occurrence of learning is difficult to quantify, and often based on indirect measures. Building on initial work presented at SRHE2016, whereby we provided initial evidence of our approach using data from one large distance learning university (Author A, 2017), in this follow-up study amongst two "traditional" universities we seek to replicate the feasibility of using assessment grades as a measure of learning gain. To do so we have performed a detailed analysis of the academic performance of individual students as described by their assessment grades. The study follows individual students across 3 years of study.

Method

Students' academic performance data was collected for 3,537 students who have graduated in summer 2016. The academic performance data was retrieved from university databases for each student starting from their first year of study until their final year of study. The dataset contained only students who have successfully completed their respective degree, and as such there were no missing observations. University 1 sample contained 1,990 students, while University 2 sample included 1,547 students. From University 1 the detailed data was obtained for each student for each semester, whereas for University 2 only overall year grades were available. The data was collected across 20 departments in each university. Although the number of departments were the same, the exact composition of subjects in the departments were slightly different, reflecting the different specialisation focus of the two universities. In line with Author A (2016), identical multilevel growth-curve models were estimated for each university in MLWiN (Rasbash, Charlton, Browne, Healy, & Cameron, 2005; Rasbash, Steele, Browne, & Goldstein, 2009). The dependent variable was students' academic performance, with a possible maximum score of 100.

Results

Table 1: *Semester and year average grade means and standard deviations across two universities across three years.*

	University 1		*University 2*	
Year	*M*	*SD*	*M*	*SD*
1	60.65	7.62	63.75	12.66
2	61.31	6.81	65.64	12.74
3	63.32	6.63	64.12	14.02

As illustrated in Table 1, for both universities average grades increased from year 1 to year 3, indicating potentially positive learning gains, although the standard deviations in grades in particular for university 2 indicate substantial variation. In order to examine students' change in performance throughout the undergraduate degree, regression, 2-level and 3-level growth curve models were estimated and compared with their fit to the data. The results are presented in Table 2, whereby the 2-level model fitted the data significantly better than the regression model, and the 3-level model fitted the data better than the 2-level model. This suggests that the present dataset has a 3-level hierarchical structure. The Beta coefficients represent the longitudinal learning gains students made throughout the degree.

Table 2: *Regression, 2-level and 3-level growth-curve modelling of undergraduate students' performance.*

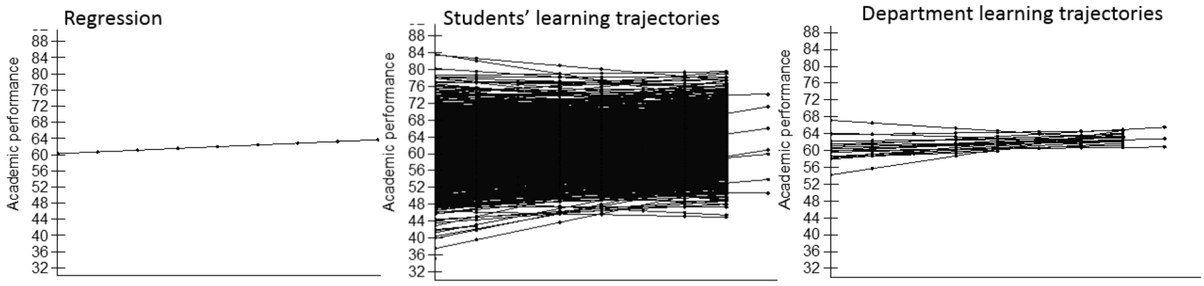
University 1						
	Regression	*S.E.*	*2-levels*	*S.E.*	*3-levels*	*S.E.*
Intercept B_0	60.252	0.114	60.2	0.16	60.337	0.687
Slope B_1	0.429**	0.027	0.422**	0.024	0.365**	0.111
Deviance	74016.17		68227.62		67983.61	
X^2 change			5788.548**		244.012**	
University 2						
Intercept B_0	64.322	0.325	64.225	0.323	63.626	1.419
Slope B_1	0.184	0.251	0.22	0.211	-0.131	0.723
Deviance	33145.79		32600.89		32255.87	
X^2 change			544.898**		345.028**	

**p<0.001

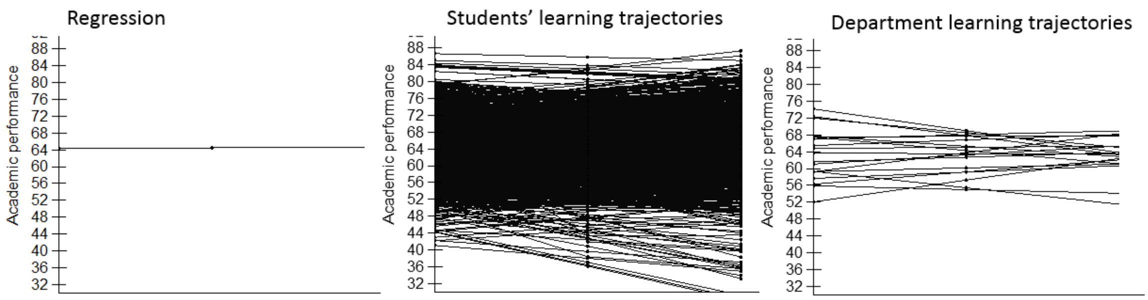
As can be seem from Table 2, although regression coefficients showed that on average students at both universities showed improvement in their standardised grade, at the University 1 the gain was significant, whereas at the University 2 the gain was not. Furthermore, when taking into account the multilevel structure of the data, the gains at University 1 remained significant and positive, whereas at the University 2 gain was slightly negative, but not significantly so. This indicates that students at University 1 make significant gains whereas at University 2 there is no significant change in student's grades. To visually illustrate the learning trajectories of students, learning trajectories of individual students were plotted and are presented in Figure 2.

Figure 2: *Learning gains per student and per department*

University 1:



University 2:



Finally, Variance Partition Coefficients (VPC) were calculated to determine how much variance each level of the model accounted for. Table 3. University 2 had more variance at the departmental level than University 1, while at the University 1 variance was mainly nested between students, whereas at the University 2 it situated within students.

Table 3: *Explained variance per level (department, between students, within students).*

	University 1	University 2
Variance at Department level	13.1%	22%
Variance between students	59.8%	22%
Variance within students (between years)	27.1%	56%

Discussion

Overall there were two key findings that have important theoretical and practical implications for estimating students' learning gains in undergraduate HE courses. Firstly, the results illustrated that when looking at the students' learning gains it is important to take the context of the university into account. Comparing learning gains in universities revealed that although both universities overall showed positive gains, when looking at the context (i.e., variance at the department level) substantial differences were present (see Table 2 and Table 3). As such, multilevel modelling is a more accurate method in comparison with simple linear models when estimating students' learning gains. The simple models are not able to detect differences between modules when looking at the department and degree level performance, whereas multilevel modelling can.

This has important implications for TEF when assessing learning gains at an institutional level, as our results indicate that aggregate learning gains estimates can result in misleading estimates of students' learning gains on a discipline or degree level. Furthermore, these results provide valuable information for universities as they outline what areas educational interventions should focus on to have an impact on students' learning gains. The limitations, applications and implications of this research will be explained during the presentation.

References

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