Projecting Continuing Student Enrolments: A Comparison of Approaches

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Higher education in Australia is undergoing a comprehensive reform with particular focus on higher levels of attainment by increasing access to university study for Australians from all backgrounds. To support the government's ambition of around 217,000 additional graduates by 2025, it has committed to removing caps and funding student places on the basis of student demand. While this approach increases the total level of funding available to universities, it comes at some expense of certainty with funding no longer available for places not filled. For universities to successfully operate in this more uncertain and competitive external environment will, more than ever, necessitate comprehensive, robust business planning based on more precise projections of student enrolments.

The University of Newcastle is a comprehensive, research-intensive university of 32,000 students that serves a regional population. It has a data warehouse that merges and links data from internal and external sources and over time to enable longitudinal analysis of the admission, progression, retention and success of cohorts of students. The university has historically used a range of data-driven approaches to project continuing student enrolments and equivalent full-time student load (EFTSL) for business planning purposes, based on the academic career, program, campus and admit term of student cohorts. This article presents the results from a comparison of these approaches with a more complex approach to projecting continuing student enrolments incorporating additional information on student demographic, admission and performance characteristics associated with retention and success.

Keywords: student load, enrolments, projections, forecasts

A comprehensive reform of higher education in Australia is in progress that involves a focus on higher levels of attainment to be achieved by increasing access to university study for Australians from all backgrounds. As part of the Commonwealth Government's proposed 10-year reform agenda to ensure a stronger and fairer Australia, it has announced its ambition for 40% of 25- to 34-year-olds to hold a qualification at bachelor level or above by 2025 (Commonwealth of Australia, 2009). It is anticipated that this will lead to around 217,000 additional graduates over this period. To achieve this goal the government has committed to the recommendation of the Bradley Review of Australian Higher Education (Bradley, Noonan, Nugent, & Scales, 2008) to remove caps on Commonwealth-supported places and

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instead fund places on the basis of student demand. To this end, an additional $491 million in funding to deliver an additional 80,000 student places will be made available to universities over the four-year period from 2009–10 to 2012–13 (Commonwealth of Australia, 2009).

While this approach increases the total level of funding available to universities, it comes at some expense of certainty, with funding no longer available for underenrolment from 2012. That is, without a 1% buffer and 4% limit on funding reductions for underenrolment, universities will no longer be able to obtain funding for places not filled. For universities to successfully operate and take advantage of the opportunities available in a more uncertain and competitive environment, comprehensive, robust planning based on accurate student load projections will be key. Yet a review of the literature within the Australian higher education sector on methods of projecting continuing load, and the comparison of methods, showed that there is a scarcity of published work however

Student enrolment or equivalent full-time student load (EFTSL) projections in Australia are generally split into two components—commencing and continuing. The Department of Education, Employment and Workplace Relations (DEEWR) consider a student as commencing in the academic year in which they first enrolled in a course of study (program) at a higher education provider, while continuing students comprise all those who are noncommencing in an academic year (DEEWR, 2010a). Continuing student load is usually projected based on historical trends and is the focus of this article, as it is often used to inform commencing student load projections in conjunction with a range of other factors, including funding targets and strategic priorities.

When projecting continuing student load it is important to recognise that there are many reasons students do not return to study the same program at an institution in the following year. They may have completed the program or taken a leave of absence, or students may have withdrawn from a program. This attrition from programs, and its converse retention, have become increasingly important to Australian universities in recent years and have been identified by DEEWR as potential indicators of performance (DEEWR, 2009a) for $206 million in new higher education performance funding available from 2010 (Commonwealth of Australia, 2009). There have been numerous quantitative and qualitative studies of student attrition and retention that have identified a range of associated demographic, admission and performance characteristics (Herzog, 2005; McInnes & James, 2004; Murtaugh, Burns, & Schuster, 1999; Perkhounkova, Mclaughlin, & Noble, 2006; Radcliffe, Huesman, & Kellogg, 2006; Stratton, O'Toole, & Wetzel, 2008). However, the findings of such studies focus on identifying opportunities and areas for improvement, rather than any potential for application in student load planning.

The University of Newcastle (UoN) is a comprehensive, research-intensive university of 32,000 students serving a regional population. It has a data warehouse that merges and links data from internal and external sources and over time to enable longitudinal analysis of the admission, progression, retention and success of cohorts of students. Historically, UoN has used a broad high-level data-driven approach to project continuing student load for business planning purposes. In recent years, however, increasingly detailed methods have been developed in an attempt to produce more accurate, higher quality student load projections. This article will compare the projection performance of these approaches with a more complex approach that incorporates additional information on student demographic, admission and performance characteristics associated with attrition, to determine the simplest approach to accurately project continuing student load.

Methods

Historical Commonwealth-supported student enrolment and load (EFTSL) records from 2004 to 2010 were extracted from the UoN data warehouse for a representative sample of 20 established semester-based Bachelor Pass programs with a range of student population sizes across the scope of disciplines taught by the university.

All records extracted from the UoN management information system (MIS) include information on student demographics such as age, sex, socioeconomic status (SES), disability status, Indigenous status, language spoken at home and area of residence; admission and enrolment characteristics such as program of study, enrolled campus, admit term (semester), basis of admission and prior study exemption; and performance characteristics such as course grades. Continuing student load was defined as all noncommencing student load as previously described.

This article considers and compares results from a variety of approaches to projecting continuing student load (Table 1), ranging in complexity from simple population-average measures to statistical regression models based on individual student characteristics. For seven approaches two alternative measures are used, and for the statistical regression approach one measure is used, resulting in a total of fifteen approaches being compared (Table 1). All approaches use historical data over a range of baselines to predict future student behaviour and thus project continuing load. Full details of approaches are provided in following sections.

Table 1

Projection Approaches and Associated Measures for Comparison

	Measure		
	Progression Rates		Number of Courses
Approach	Load	Enrolment	
Steady State	1	2	
Commencing / Continuing	3	4	
Admit-Year Cohort	5	6	
Admit-Year Cohort: Adjusted for Prior Study	7	8	
Admit-Term Cohort	9	10	
Admit-Term Cohort: Adjusted for Prior Study	11	13	
Program-Year: At Start of Year	13	14	
Regression			15

Steady State Approach

The simplest approach to projecting continuing student load is to estimate next-year continuing student load as a function of previous-year student load. This typically takes the form of a percentage allowed to range from 0 to 100% calculated from historical baseline data. This aggregate measure, often referred to as a load progression rate, is designed to capture the likely impact of student attrition, completions and those returning from a leave of absence on continuing student load, as well as the effect of changing patterns in average student load per enrolment (Approach 1). A potential issue with this approach is the lack of a conceptual link between one EFTSL in the previous year and one EFTSL in the next year, which may come from different numbers of enrolments due to a combination of attrition and changing average student load per enrolment. Such a dense measure of student behaviour can also be complex to unpack and difficult to explain in terms familiar to university faculty and executive staff. A possible alternative is to calculate enrolment (rather than load) progression rates to project next-year continuing student enrolments and multiply the result by average EFTSL per enrolment to estimate continuing student load. This separates the effects of attrition, completions and returning leave of absence from that of changing patterns in average student load and is conceptually much simpler to communicate (Approach 2).

Commencing/Continuing and Admit-Year Cohort Approaches

A potential issue with the previous approach is the often unrealistic assumption that program intakes are largely identical from one year to the next. This is an issue because student intakes can and do vary greatly from year to year and also from term to term for many reasons, including student demand, resource constraints and strategic priorities. For example, a program may have no mid-year intake followed by a large mid-year intake before reverting to a small mid-year intake (Figure 1).

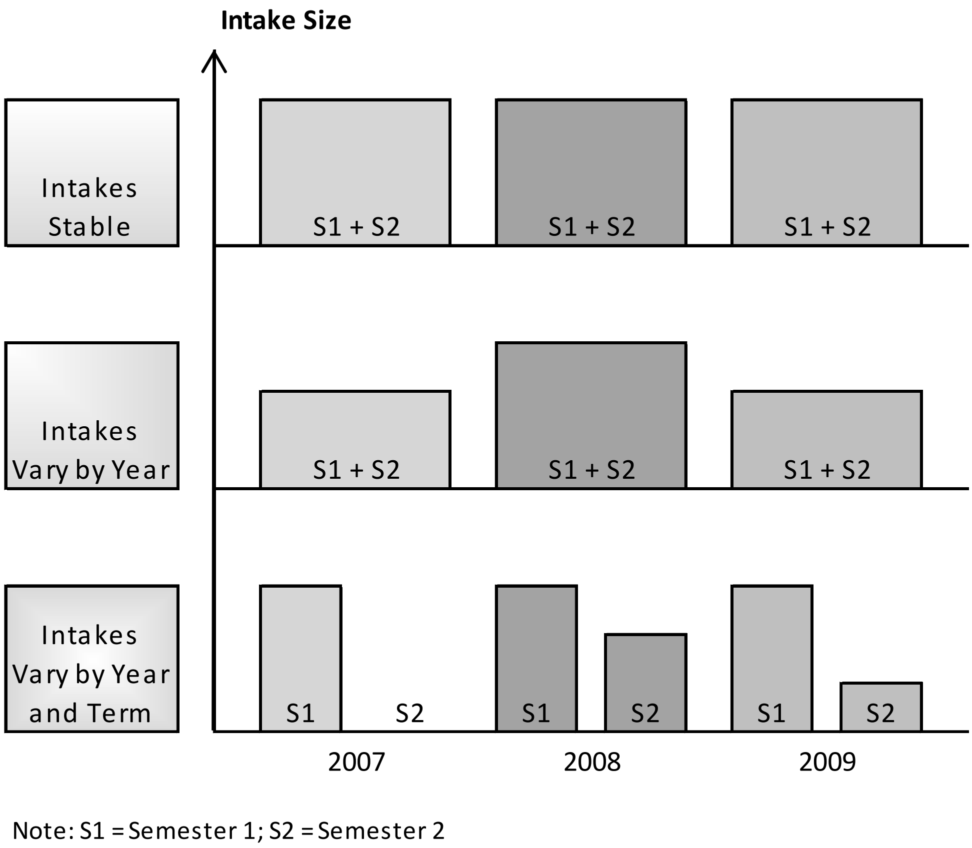

Figure 1

Assumed student intake by approach to projecting continuing student load.

The simplest way to capture variation from year to year in continuing student load projections is to calculate progression rates separately for commencing and continuing student load and enrolments (Approaches 3 and 4). A more comprehensive method involves categorising students into cohorts based on their admit year and calculating separate progression rates for each cohort (Approaches 5 and 6). Next-year continuing student load is then projected by commencing/continuing status or admit-year cohort as a function of previous-year student load or enrolments, both of which adjust for changing student intakes by year. To ensure adequate numbers for calculations, admit-year cohorts with less than 5% of total student load were combined. An additional complicating factor is that students can commence a program with prior study exemption, which can lead to students with identical admission years but considerably different course requirements to complete a program. A possible extension to the admit-year cohort approach that attempts to account for this involves adjusting a student's admit-year cohort based on the estimated number of years needed to obtain the prior study exemption, given their average student load per term since commencing (Approaches 7 and 8). For example, a student with an admit term of semester 1, 2009, with 0.500 EFTSL prior study exemption who has taken 0.500 EFTSL per term on average would have their admit-year cohort adjusted to 2008.

Admit-Term Cohort Approach

To capture variation from year to year and term to term (Figure 1) in next-year continuing student load projections, it is necessary to categorise students into cohorts based on admit term. Separate progression rates are then calculated for admit-term cohorts, with next-year continuing student load projected by cohort to adjust for changing student intakes by year and terms (Approaches 9 and 10). When programs have only one admit-term cohort per year, progression rates are the same as for admit-year cohorts. To ensure adequate numbers, admit-term cohorts from admit-year cohorts with less than 5% of total student load were combined. Similar to the admit-year cohort approach, this approach can also be extended to adjust for prior study exemption, only on a term-by-term basis (Approaches 11 and 12).

Program-Year Approach

An issue with the admit-year and admit-term cohort approaches discussed above is that they use time since admission as a proxy for student progression, essentially assuming that students admitted to a program at the same relative point in time have progressed at the same rate. An approach that eliminates this assumption from calculations involves categorising students into program years based on their actual progression, regardless of when they were admitted. For example, students enrolled in a 3-year full-time program are classified as 1st, 2nd or 3rd year students based on the amount of completed EFTSL at the start of each academic year, assuming 1.000 EFTSL per program year. The major benefits of such an approach compared to others are that it only combines students at similar stages of programs and explicitly accounts for students' prior study exemption, unlike the approximate adjustment previously described (Approaches 13 and 14).

Statistical Regression Models Approach

None of the approaches to projecting continuing student load presented thus far directly account for students' demographic and performance characteristics, instead assuming that they are consistent from year to year. An alternative, more flexible, but considerably more complex approach with the capacity to adjust for such characteristics, is to fit statistical regression models to student enrolment and load data. While a range of linear or generalised linear regression models could potentially be used, Poisson or negative-binomial regression models are particularly appropriate given that predictions are restricted to non-negative values (as opposed to linear regression) and student load can be projected directly from predicted values (as opposed to logistic regression). Since Poisson and negative-binomial regression are both used to model count data, student load must be parameterised as the number of courses taken by students based on a standard student load per course, in this case 0.125 EFTSL. In this approach, historical baseline data is used to build models, which are then applied to previous-year student data to project the number of courses taken in the next year, multiplied by 0.125 EFTSL to estimate continuing student load (Approach 15).

In this study, Poisson and negative-binomial regression models were fitted separately by program, with the best fitting model used for projections. A range of indicator variables for student characteristics, potentially predictive of continuing student load and readily available in enrolment and load records, were included in all models, except when there were insufficient data. This included variables describing students' sex, age, disability status, Indigenous status, SES, area of residence, average load per term, semester 2 enrolment status, remaining load to complete program, courses failed or withdrawn and grade point average (GPA). A limitation of this approach is that it is not easy to account for load taken by continuing students who were on leave of absence or otherwise not enrolled in the previous year. Since load taken by such students constitutes only a very small share of total continuing student load, however, in this study a small amount of load was simply imputed for each program using historical baseline data.

For each of the fifteen approaches described (Table 1), consideration must also be given to the most appropriate length of historical baseline for projecting continuing student load given the trade-off between sample size and sensitivity to current student behaviour. To this end, baselines of between one and three years have been used to calculate student load and enrolment progression rates and construct regression models (Table 2). This gives a total of 45 approach and historical baseline combinations for comparison and evaluation in 2008, 2009 and 2010 across all 20 programs in the sample.

Table 2

Approaches and Associated Measures for Comparison

Projection Year	Historical Baseline	Baseline Years 2004	2005	2006	2007	2008	2009
2008	1 Year			←	→		
	2 Years		←	—	→		
	3 Years	←	—	—	→		
2009	1 Year				←	→	
	2 Years			←	—	→	
	3 Years		←	—	—	→	
2010	1 Year					←	→
	2 Years				←	—	→
	3 Years			←	—	—	→

In each case, the performance of projections was assessed by evaluating the projection error, calculated as the differences between actual and projected student load. Approach and baseline combinations were ranked and compared according to the absolute value of the projection error in each year and across the entire study period. Relative projection errors calculated by expressing absolute projection errors as a percentage of total continuing student load were used to assess the size of projection errors in student load terms, given that student load varied considerably across programs.

Results

In the period 2008 to 2010, a regression approach with a three-year baseline produced the lowest median projection error rank (15) among the 45 approach and historical baseline combinations across all 20 programs, and ranked better than 6.5 in 25% of programs and better than 32 in 75% of programs. The median rank of this approach was somewhat variable across individual years however, being higher in 2008 (12) and 2010 (14) but considerably lower in 2009 (21) (Table 3). The median relative projection error of this approach from 2008 to 2010 indicates that half of all projections were within 5.3% of actual continuing student load, while 25% were within 2.5% and 75% within 8.3% (Table 4). The same approach with a two-year baseline produced very similar median rank (16) and a tighter interquartile range (IQR) of 9.0–30.5. The relative projection error of this approach was actually better than the three-year approach, with a median of 4.4% and IQR or 2.4%—8.0% over the study period and slightly more consistent from year to year.

The projection rate approaches with the lowest median projection error ranks were admit-year cohort load progression rates (LPR) with two- (17) or three-year (17.5) baselines, and program-year load progression rates with a two-year baseline (17.5) or enrolment progression rates (EPR) with a one-year baseline (18). Of these, the admit-year cohort LPR approach with a two-year baseline had the most narrow rank IQR (10–24.5) while the program-year EPR approach with a one-year baseline had the widest rank IQR (8–32). In relative terms, the best performing approach was the program-year LPR approach with a two-year baseline (median = 4.4%; IQR 2.1%–8.2%) followed closely by both admit-year cohort approaches and then the program-year one-year EPR approach (median = 6.0%; IQR 2.0%–9.4%).

Tables 4 and 5 show that the admit-term cohort approach generally performed slightly below than the admit-year cohort approach in both absolute and relative projection error terms. For both of these approaches, LPR often performed considerably better than EPR and adjustments for prior study exemption consistently produced worse results, particularly in the case of LPR. The program-year approach typically performed very similarly to the admit-year cohort approach, although EPR performance was much closer to LPR performance. The steady state and commencing/continuing approaches generally performed poorly when compared with other approaches for both LPR and EPR. Although the two- and three-year baseline regression approaches both ranked highly, there was also a noticeable decline in projections performance with the shorter one-year baseline. This is similar to all other approaches where one-year baselines consistently produced worse results than longer baselines.

Table 3

Median and Inter-Quartile Range Projection Error Ranks Across the 20 Bachelor Pass Programs in the Study Sample by Approach, Historical Baseline and Projection Year

Approach		Measure	Historical Baseline	2008 Median	2009 Median	2010 Median	2008–2010 Median	2008–2010 Q1	2008–2010 Q3
1	Steady State	Load	1 Year	25.0	32.5	28.5	27.5	14.0	39.5
			2 Years	19.5	26.5	28.5	25.0	13.0	36.0
			3 Years	19.5	28.0	27.0	26.5	12.5	38.0
2		Enrols	1 Year	24.5	31.0	28.0	28.0	17.0	39.0
			2 Years	20.5	30.5	25.0	26.5	15.0	37.0
			3 Years	30.0	28.5	20.5	27.0	14.5	37.0
3	Commencing/ Continuing	Load	1 Year	19.5	27.5	25.0	25.5	11.0	37.0
			2 Years	17.0	22.5	28.5	22.5	11.5	34.0
			3 Years	14.0	26.0	22.0	22.0	10.5	32.0
4		Enrols	1 Year	22.5	26.5	28.5	26.5	16.0	37.5
			2 Years	25.5	27.0	25.0	26.0	18.5	33.5
			3 Years	23.5	20.0	26.5	23.0	8.5	34.0
5	Admit-Year Cohort	Load	1 Year	18.0	19.0	19.0	19.0	10.5	33.5
			2 Years	18.0	16.5	18.0	17.5	10.0	24.5
			3 Years	19.0	19.5	15.0	17.0	9.0	27.0
6		Enrols	1 Year	28.5	20.0	16.5	21.5	12.5	34.0
			2 Years	28.5	23.5	22.0	24.5	16.5	34.0
			3 Years	33.0	30.0	20.5	25.5	9.5	37.0
7	Admit-Year Cohort —Adjusted for Prior Study	Load	1 Year	16.5	32.5	24.5	26.0	12.0	34.5
			2 Years	21.5	15.0	25.5	21.5	11.0	28.5
			3 Years	19.0	18.0	21.5	19.0	11.5	27.5
8		Enrols	1 Year	30.0	24.0	25.5	27.0	13.5	35.5
			2 Years	25.5	21.5	26.0	24.5	16.0	34.0
			3 Years	21.5	24.0	24.5	23.5	13.5	34.0
9	Admit-Term Cohort	Load	1 Year	21.0	20.5	24.0	21.0	9.0	32.0
			2 Years	22.0	16.5	17.5	19.0	11.0	27.5
			3 Years	21.0	20.0	18.0	19.5	11.0	29.0
10		Enrols	1 Year	26.0	21.0	18.5	21.0	11.5	34.0
			2 Years	31.0	28.5	20.0	27.0	17.0	37.5
			3 Years	30.5	30.5	19.0	26.5	10.0	37.5
11	Admit-Term Cohort —Adjusted for Prior Study	Load	1 Year	21.5	33.0	25.5	32.0	16.5	37.5
			2 Years	26.0	22.5	29.0	26.0	14.5	33.5
			3 Years	23.5	16.5	21.5	22.0	12.5	31.0
12		Enrols	1 Year	34.0	32.5	33.0	33.5	15.5	39.5
			2 Years	35.0	26.5	31.0	30.0	19.0	39.0
			3 Years	32.0	26.0	21.0	28.0	18.0	37.5
13	Program-Year —At Start of Year	Load	1 Year	12.0	21.5	23.0	19.5	5.0	32.0
			2 Years	13.0	16.0	20.5	17.5	10.0	27.0
			3 Years	19.5	21.0	15.5	19.0	8.5	31.0
14		Enrols	1 Year	18.5	18.0	19.0	18.0	8.0	32.0
			2 Years	24.5	16.5	20.0	22.5	8.0	32.5
			3 Years	25.5	19.0	19.5	23.5	8.0	33.5
15	Regression	Number of courses	1 Year	17.5	22.0	18.5	20.5	11.5	35.0
			2 Years	13.5	18.5	18.0	16.0	9.0	30.5
			3 Years	12.0	21.0	14.0	15.0	6.5	32.0

Note: Lower rank is better

Table 4

Median and Inter-Quartile Range Relative Projection Errors Across the 20 Bachelor Pass Programs in the Study Sample by Approach, Historical Baseline and Projection Year

Approach		Measure	Historical Baseline	2008 Median	2009 Median	2010 Median	2008–2010 Median	2008–2010 Q1	2008–2010 Q3
1	Steady State	Load	1 Year	5.9%	6.6%	11.4%	7.7%	2.9%	12.6%
			2 Years	4.7%	7.6%	9.2%	7.6%	2.7%	12.4%
			3 Years	5.3%	5.9%	7.2%	6.0%	2.9%	12.8%
2		Enrols	1 Year	4.8%	7.1%	9.2%	7.1%	3.5%	13.7%
			2 Years	5.9%	6.4%	9.5%	6.9%	3.5%	12.8%
			3 Years	5.8%	4.8%	6.4%	5.6%	3.3%	11.8%
3	Commencing/ Continuing	Load	1 Year	3.7%	6.8%	10.9%	6.8%	2.2%	12.4%
			2 Years	3.4%	6.8%	7.6%	6.5%	2.3%	10.8%
			3 Years	3.0%	4.3%	8.3%	4.7%	2.5%	10.4%
4		Enrols	1 Year	4.7%	6.1%	9.5%	6.0%	3.6%	15.2%
			2 Years	6.0%	6.8%	8.3%	6.6%	3.9%	12.3%
			3 Years	5.0%	4.5%	6.6%	5.7%	2.0%	10.7%
5	Admit-Year Cohort	Load	1 Year	4.3%	5.7%	7.5%	5.3%	3.1%	8.9%
			2 Years	4.8%	3.9%	6.7%	5.0%	2.3%	8.5%
			3 Years	4.1%	4.4%	6.0%	4.6%	2.2%	8.5%
6		Enrols	1 Year	7.3%	5.0%	5.2%	5.3%	3.1%	9.8%
			2 Years	7.9%	5.0%	6.1%	6.3%	3.6%	10.4%
			3 Years	6.8%	5.5%	6.8%	6.0%	3.4%	10.5%
7	Admit-Year Cohort —Adjusted for Prior Study	Load	1 Year	4.6%	7.9%	8.3%	5.9%	2.9%	11.5%
			2 Years	4.4%	2.9%	7.6%	4.5%	2.1%	9.5%
			3 Years	4.6%	4.6%	7.3%	6.1%	2.3%	9.6%
8		Enrols	1 Year	6.7%	6.6%	8.2%	7.2%	2.5%	11.8%
			2 Years	6.5%	5.2%	7.7%	5.8%	3.8%	10.1%
			3 Years	6.6%	5.3%	8.1%	6.5%	3.6%	9.8%
9	Admit-Term Cohort	Load	1 Year	4.5%	4.8%	6.7%	4.7%	3.1%	8.6%
			2 Years	6.4%	3.0%	5.3%	4.7%	2.1%	9.7%
			3 Years	5.4%	3.5%	6.2%	5.2%	2.7%	8.6%
10		Enrols	1 Year	7.4%	4.1%	5.8%	5.6%	3.5%	10.1%
			2 Years	7.9%	5.1%	6.0%	6.3%	3.6%	11.7%
			3 Years	6.7%	6.3%	7.3%	6.7%	3.2%	11.3%
11	Admit-Term Cohort —Adjusted for Prior Study	Load	1 Year	5.7%	8.1%	9.2%	7.7%	3.2%	11.4%
			2 Years	6.6%	4.4%	9.1%	7.3%	2.6%	11.3%
			3 Years	6.1%	5.7%	7.7%	6.3%	3.0%	10.1%
12		Enrols	1 Year	7.5%	7.8%	8.2%	7.7%	4.2%	13.7%
			2 Years	9.4%	6.0%	9.1%	8.5%	4.6%	11.8%
			3 Years	7.8%	7.3%	8.5%	7.6%	3.9%	11.6%
13	Program-Year —At Start of Year	Load	1 Year	5.9%	4.2%	8.4%	5.7%	1.9%	9.2%
			2 Years	5.2%	3.2%	7.1%	4.4%	2.1%	8.2%
			3 Years	3.9%	4.5%	6.6%	4.7%	2.0%	8.9%
14		Enrols	1 Year	5.9%	4.7%	7.1%	6.0%	2.0%	9.4%
			2 Years	7.3%	4.0%	5.6%	5.9%	2.4%	10.8%
			3 Years	7.0%	5.4%	5.6%	6.2%	2.8%	9.6%
15	Regression	Number of courses	1 Year	4.7%	5.8%	8.9%	6.1%	2.7%	10.1%
			2 Years	4.1%	4.0%	5.7%	4.4%	2.4%	8.0%
			3 Years	4.1%	6.4%	5.5%	5.3%	2.5%	8.3%

Note: Lower percentage is better

Although regression models were not built for inference, results indicated that semester 2 is a powerful predictor of continuing student load. Selected results from a subanalysis of progression rate approaches incorporating students' semester 2 enrolment status are shown and compared in Table 5. It shows that performance improved for both the admit-year cohort and program-year approaches across all historical baselines when this is taken into account, producing even more accurate results than the regression approach.

Table 5

Selected Approach and Historical Baseline Combinations Incorporating Semester 2 Enrolment Status and End of Year Progression Relative Projection Errors by Projection Year

			2008–2010					
			Exc. Semester 2 Status			Inc. Semester 2 Status		
Approach	**Measure**	**Historical Baseline**	**Median**	**Q1**	**Q3**	**Median**	**Q1**	**Q3**
Admit-Year Cohort	Load	1 Year	5.3%	3.1%	8.9%	4.5%	2.5%	8.6%
		2 Years	5.0%	2.3%	8.5%	4.3%	2.2%	9.3%
		3 Years	4.6%	2.2%	8.5%	4.1%	2.1%	8.4%
Program-Year —At Start of Year	Load	1 Year	5.7%	1.9%	9.2%	5.0%	1.6%	8.4%
		2 Years	4.4%	2.1%	8.2%	3.8%	1.9%	7.8%
		3 Years	4.7%	2.0%	8.9%	4.0%	2.3%	8.3%
Regression	Number of courses	1 Year	-	-	-	6.1%	2.7%	10.1%
		2 Years	-	-	-	4.4%	2.4%	8.0%
		3 Years	-	-	-	5.3%	2.5%	8.3%

Discussion

In a changing Australian higher education environment, accurate student load projections will be imperative for comprehensive, robust planning that enable universities to successfully operate and take advantage of new opportunities. Although emphasis is often placed on commencing students, accurate continuing student load projections are arguably more important for Commonwealth-supported student planning purposes as they form a larger share of total student load and, in many cases, are used to determine commencing student load projections. This article has presented the results from an evaluation of a range of simple and more complex approaches to projecting Commonwealth-supported continuing student load over recent years, with the aim of identifying the approach with the most accurate projections.

The regression approach, with a two- or three-year baseline, produced the most accurate projections over the study period in terms of absolute and relative projection errors. However, there are two primary issues with this approach. The first is that it is considerably more complex and time-consuming to fit Poisson and negative-binomial regression models than to calculate progression rates and, in many cases, models could clearly benefit from being specifically tailored to programs. A second issue is that models can only be run after course results from the final term in the current year are available, if current enrolment and performance characteristics are to be included. For these reasons, such models are not suitable for projections more than one year ahead, and then only once the current academic year is complete. Conceptually, much simpler approaches that performed almost as well as regression approaches were the admit-year cohort and program-year LPR approaches with two- or three-year baselines. An additional advantage of these approaches is their ease of use and suitability for future-year projections at any point throughout an academic year. Additional analysis showed that these approaches performed even better than regression when student's semester 2 enrolment status can be incorporated in progression rate calculations.

A potential limitation of this study is that approaches were only evaluated for Commonwealth-supported student load in Bachelor Pass programs. As such, the findings cannot be extended to other student types or academic careers. This includes international students who often enter with considerable prior study exemption and primarily study full-time, or postgraduate coursework programs that often involve shorter, trimester-based programs studied part-time. It is for the latter in particular that approaches such as admit-term cohort and a more detailed variation on the program-year approach may produce more accurate projections. This represents a valuable area of future analysis and a natural progression from Commonwealth-supported Bachelor Pass programs student load, as this comprises the majority of total student load at most Australian universities (DEEWR, 2010b).

Conclusion

This article has shown that relatively simple approaches to projecting continuing student load such as admit-year cohort and program-year load progression rates based on two- or three-year historical baselines generally perform well and produce very similar results to considerably more complex regression models. Such methods are suitable for projecting next-year and future-year continuing student load projections at any time throughout the academic year, and provide a solid basis for universities student load planning activities.

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