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**An Experimental Evaluation of a Proactive Pastoral Care Initiative
Within An Introductory University Course**

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Abstract

Improving student retention and academic performance is a key objective for higher education institutions, and finding effective interventions for assisting with at-risk students is therefore important. In this paper we evaluate a proactive pastoral care intervention that was trialled in an introductory economics course. We first identified students at high risk of failure, and then randomised these students into two treatment groups and a control group. The first treatment group received an email with information about academic support, while the second treatment group received the email as well as a personal telephone call to follow up. In evaluating the impact of the intervention trial, we found that the first intervention did not significantly improve student outcomes, but the second intervention did improve outcomes in one of the two semesters evaluated. However, the statistically insignificant results were positive and statistical insignificance may be due to a lack of statistical power. Overall, the initiative was a qualified success. It is both simple and cost-effective, and should be considered for wider implementation and further evaluation.

Keywords

academic performance
pastoral care
student retention
randomised-controlled trial
New Zealand

JEL codes

A22, I21

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1. Introduction

Despite the best intentions of academic and support staff in higher education institutions, every semester a number of students will fail courses and/or withdraw from programmes of study. Often, this is through no fault of the student or the institution. However, at other times the institution may be failing to provide students the support necessary to successfully complete their studies. Understanding the reasons for students' poor academic progress, and designing appropriate and effective interventions to improve student performance, are clearly an imperative for higher education institutions. Indeed James, Krause and Jennings (2010) have argued that 'there is perhaps no greater challenge facing the [higher education] sector than that of identifying and monitoring the students who are 'at risk' of attrition or poor academic progress' (p. 6).

Providing early intervention services to students identified as being at high risk of failing an introductory university course is desirable for a number of reasons. First, students' costs (both direct and indirect) of completing their programmes of study are reduced when they don't have to repeat courses and don't have to stay enrolled for longer than the 'normal' duration of their programmes. Early intervention may help to ensure that students are financially more able to complete their programme of study. Secondly, students who pass early courses are more likely to stay enrolled and to complete their programmes of study than students faced with the prospect of longer than planned period of study (Tinto 2006, Tinto 1987, Terenzini and Pascarelli 1980). Thirdly, students who pass early courses are more likely to be retained in their original programmes of study and not be lost to other programmes or other institutions, saving on the institutions' administrative costs associated with transfers of credit. Fourth, high completion/retention rates may have positive consequences for the funding of public institutions (Attrie, Johnston and Livermore 2014, Campbell and Hussey 2014). Higher completion or retention rates or measures of student engagement are increasingly being used as a metric for funding allocations (Zepke and Leach, 2010). Fifth, high student success rates may enhance the reputations of both the lecturers and their schools/departments, and ultimately their institutions. Reputational effects are important as higher education becomes increasingly more competitive (Nguyen and LeBlanc 2001). The benefits of providing learning support services are thus numerous, and accrue not only to students, but also to teachers, and their institutions.

Most tertiary education institutions provide some form of academic and other support services to help students who are encountering difficulties with their studies, and students are generally encouraged to access these services when they need them. Typically, these services are based on self-referral, that is, the student must recognise a need to seek additional help and know how to access the appropriate support services. Despite information about these services often being widely available, not all students in need will access them. Students who are highly motivated are more likely to access academic support services, while disengaged students are less likely to (Nichols 2010, Nash 2005, Barefoot 2004). As such, the students

who most need academic and other support services tend to be the ones that do not actually access them. This diminishes the effectiveness of the services, not necessarily because the services do not work, but because the students that need them most do not utilise them.

The problems associated with self-referral could be avoided by proactively identifying students at higher risk of non-completion of programmes of study, early in each semester, and directing additional tailored support towards those students. This type of ‘proactive pastoral care’ is relatively uncommon, and the success (or otherwise) of these initiatives has rarely been empirically tested. Moreover, there is no clear guidance as to whether these initiatives should be undertaken for individual courses (that is, students’ performance identified early in individual courses), or only at the level of programmes of study as a whole.

The proactive pastoral care initiative we evaluate in this paper is primarily an attempt to increase student engagement and student retention. Our observation is that many students who fail to complete courses have often been disengaged from the beginning, not attending classes or completing assigned readings or coursework. Some of these students will engage later in the semester, but many will delay this engagement until it is too late to have an appreciable impact on overall performance in the course. A lack of engagement among introductory-level students may arise because many students who are just starting their tertiary studies experience a substantial culture shock (Christie, Tett, Cree, Hounsell and Mccune 2008). This culture shock can occur because many students, particularly those who are the first in their family to attend university, lack the necessary social or cultural capital to engage with or fit into the university learning culture (Lawrence 2006). Mann (2001) discusses this alienation that students may experience when entering the university environment. She notes that:

‘...the person who registers as a student in a higher education institution enters a pre-existing discoursal world in which they are positioned in various ways (as student, learner, competitor, debtor, consumer etc.), and in which more powerful others (lecturers, more experienced students etc.) have greater facility, knowledge and understanding of higher education discursive practices. From this perspective, the student is estranged from the language, culture and practices of the context in which they now find themselves, and is reduced, by their position in the discourse as first-year student, to a type rather than to an individual... Most students entering the new world of the academy are in an equivalent position to those crossing the borders of a new country — they have to deal with the bureaucracy of checkpoints, or matriculation, they may have limited knowledge of the local language and customs, and are alone.’
(Mann 2001, pp.10-11).

Facing this alienation, students may find it safer to avoid engaging with their tertiary studies. Moreover, some students may suffer from ‘imposter syndrome’, wherein they feel a sense of not belonging or being deserving of university study (Brookfield 1991). To

overcome these problems of alienation and 'imposter syndrome', institutions or lecturers need to foster a sense of belonging in their students, such that the students can feel safe in engaging with their studies (Bryson and Hand 2007, Kember, Lee and Li 2001). Importantly, engagement is not just about the actions of students. As Nystrand and Gamoran (1991, p.284) note, engagement 'depends on what teachers and students do together'. Moreover, engagement is about building a relationship between lecturers and students that makes students feel valued (Bruning 2002).

The starting point for building relationships between students and lecturers is making meaningful contact with students. For instance, one of the responses that Mann (2001) suggests for dealing with students' feelings of alienation is through hospitality:

'We can remember to welcome new members of our community and to help them feel at home, as we would any visitor or stranger to our own home. Metaphorically, we can provide shelter and nourishment, maps, recommendations for good places to visit, and translations and explanations of strange customs and language.' (Mann 2001, p.17).

Our proactive pastoral care initiative is based on a simple principle of making students feel valued and develop a sense of belonging, through establishing a connection between the student and staff (or a senior student). Our initiative (described in more detail below) starts with a simple personalised email to check in on students who we have identified as being high-risk. Basic strategies such as simply establishing a line of communication with the student may be all that is required to increase student retention (Berger and Braxton 1998). At the very least it demonstrates a willingness to follow up on the student and may make the student feel valued, rather than their simply being another face in the crowd of a large lecture theatre. Nurturing a relationship between the student and the lecturer or the institution is critical. Kahu (2013) notes that good relationships foster student engagement, which in turn leads to better grades and motivates students to participate. Finn (1993) argues similarly, albeit beginning at the primary school level, that participation in classroom and other activities can initiate a virtuous cycle of increased belongingness and more participation.

Pastoral care works best when it is directed at the 'right' students, that is, those that are in most need of assistance. However, identifying students likely to fail a course is not easy, especially in a large introductory level paper where most students are likely to be unknown to the lecturers, and especially early in the course when intervention would be most effective. Moreover, it is almost impossible for lecturers to effectively monitor individual student attendance in large lecture settings. It is even harder to identify students at significant risk of failure prior to substantial pieces of assessment being undertaken. Waiting until the first substantial piece of assessment, which may be a mid-term test, assignment or essay, risks leaving the identification too late for effective intervention. Poor performance in substantial pieces of assessment may discourage students from continuing with the course, or lead students to believe that they are incapable of doing well in the course and thus reduce their

effort in order to concentrate on other courses where they feel they have a greater chance of success. This inevitably leads to reduced chances of success in the course. Our proactive pastoral care initiative (described below) ensures that intervention can be made early in the semester, before substantial items of assessment fall due.

In this paper, we report on an innovative experiment to improve student performance in a fairly large (approximately 300 students) first year university course in economics. Specifically, we implement a randomised controlled trial (RCT) of a proactive pastoral care intervention within this course, then evaluate its effectiveness in terms of the successful completion of the course (i.e. the pass rate). To avoid the issues associated with student self-referral to learning support services, students at high risk of failure are identified early in the course. We then randomly assigned them to one of two treatment groups, or to a control group, in order to evaluate the impact of the intervention.

2. Literature Review

Most universities, and other higher education institutions, tend to provide learning support services to students. The types of services provided differ depending on the type of institution and education provided. The most common, however, tend to be in the form of extra tutorial assistance, academic counselling, and learning support services targeted at individual students. Some examples include interventions aimed at particular groups of students such as those making the transition into university. For instance, Queensland University of Technology's *Start Smart* programme supports undergraduate students who have not completed Year 12 within the two years prior to enrolment (Bennett and Medew 2012), while Charles Sturt University provides support for repeated fail students in distance education (Attrie, Johnston and Livermore 2014). The Charles Sturt University programme resulted in higher retention and success rates for students who experienced the intervention compared to similar students who did not.

Similarly, the Freshman Empowerment Program at Central Michigan University targets new students from low-income families and/or who are first-generation college attendees. An evaluation of this program by Folger, Carter and Chase (2004) found that students that took part in this programme had a significantly higher GPA than similar students who chose not to be involved. Williford (1997) reports on an intervention program to retain freshmen at Ohio University. The program identified freshmen likely to leave Ohio University at the end of their first year and intervened to try and retain them. Overall, freshman retention increased from 72 percent in 1982 to 83 percent in 1995 with early-identified potential leavers having the highest return rates. More recently, Campbell and Hussey (2014) reported evidence of the effects of an early intervention programme on economics student achievement at the University of Memphis. Although the Memphis programme involves students at all levels, not just first-year students, its intention is similar – that of improving student achievement

through early intervention. They reported that students who were reported for early intervention received final grades that were on average almost 4.3 percent higher than those who were not reported.

It is clear from these initiatives that there is wide acceptance, in universities and other higher education institutions, of the need to improve student performance by offering learning support services. It is also clear that there are difficulties associated with identifying students, especially in large classes, who should be offered intervention services in a timely manner. This leads to a need for creative and innovative ways of using available data to identify at-risk students (Simpson 2004). For instance, Macfadyen and Dawson (2010) encourage the use of data available in web-based Learning Management Systems to highlight student academic performance in order to identify students at-risk of failing. Similarly, Campbell, DeBlois and Oblinger (2007), and Campbell and Oblinger (2007) advocate for 'Academic Analytics' - the use of information from Academic Information Systems in combination with statistical methods to identify students who may face academic difficulties. As one example, Campbell, Finnegan and Collins (2006) used regression analysis of student performance and selected online activity data and found that SAT scores were mildly predictive of future student success. They recommended that institutional data be used to develop 'early warning' reporting tools that flag at-risk students.

As these studies show, being proactive is important because this allows the intervention to reach students who may not have otherwise sought academic support services for themselves. It also demonstrates to students that the institution cares about their performance and is willing to help them successfully complete their course or programme of study, even though they may be just one of many in a very large class. This may lead to greater student engagement and better academic performance.

3. Study Setting and the Intervention

The University of Waikato is a mid-sized university (approximately 12,000 students) in New Zealand, located in Hamilton (with a population of approximately 150,000). Waikato Management School is a Triple Crown accredited business school within the university that offers a four-year management degree alongside three-year specialist degrees. The four-year management degree and a three-year specialist degree in business analysis include a compulsory first-year course in microeconomics within the core of the programme of study. This course is offered two or three times per year, and each semester has between 300 and 350 students enrolled.

The course has neither an atypically high nor low pass rate – on average approximately 80 percent of enrolled students will pass the course in any given semester. Prior to the intervention experiment, there was no course-specific pastoral care initiative in place, although the teaching staff have weekly office hours available for students to seek additional

help, and the university provides centrally-organised learning support services that students have ready access to. However, these pre-existing services necessarily require that students take the initiative to access them. Prior to the intervention experiment, there was no coordinated mechanism or system for identifying and referring at-risk students to learning support services.

The proactive pastoral care intervention was undertaken in the first semesters of the 2013, and 2014 academic years. Both semesters were sixteen weeks long, with an initial six weeks of teaching, followed by a two-week teaching recess, then a further six weeks of teaching, and finally a three week study and examination period. Each student is requested (but not required) to sign up for a weekly tutorial group (there are many tutorial groups available, on different days and at different times, for students to choose from). Tutorial sessions begin in the second week of the semester. Attendance is recorded at tutorials, and is incentivised by contributing a small proportion to students' overall grades. Students also complete weekly online tests that form part of the overall assessment of the paper, beginning from the end of the second week. Finally, students who are present in the second lecture of the first week of the semester complete an economic literacy test (Cameron and Lim 2015). The first substantial item of assessment is a mid-semester test that is held in the fifth week of the semester, and which contributes 15 percent of each student's overall grade.

It was felt that waiting until the fifth week (at the time of the mid-semester test) to identify students at risk of failing the paper was too late for effective intervention. Instead, we sought to identify students at risk by the end of the fourth week of the semester, such that any intervention might be implemented before the mid-semester test was held. Thus, only data that were readily available at that time could be used in this model. This included basic programme of study data (citizenship (domestic/international); and programme of study) and course-specific data (whether they had signed up for a tutorial; attendance at each of the first three tutorials; whether they had signed up for the online testing system; completion of each of the first three online tests; and completion of the economic literacy test in class in the first week). The combination of programme of study and behavioural data is important, as student behaviour within courses has been found to be instrumental in contributing to a range of outcomes including persistence, satisfaction, achievement and academic success, as well as being good indicators of student engagement (Krause and Coates 2008, Pascarella and Terenzini 2005, Astin 1999).

Two further categories of data, reflecting student demographics (gender, age), and student aptitude, were considered. Student performance in prior courses, or their performance in high school, are likely to be good indicators of academic performance. However, due to institutional privacy rules these (demographic and student performance) data are not broadly available to teaching staff at the University of Waikato, although staff with administrative responsibilities (such as qualification convenors, subject convenors, or heads of department) can access them. While an institutional-level model of student risk of failure could potentially

perform better using student demographic and academic performance data, as a demonstration tool for academic staff we instead used data that would be readily available to course lecturers without the need to request additional institutionally-held data.

Following the identification of appropriate data, a logistic regression model was developed based on student data from the first semester of 2012 (see results, Section 5). This model was then used to identify students at high risk of failure in 2013 and 2014.

The experimental proactive pastoral care intervention was explicitly designed as a randomised controlled trial (RCT). RCTs are the ‘gold standard’ in impact evaluation, since they potentially ensure that all observed and unobserved confounders are controlled for through the process of randomisation into treatment and control groups (Torgerson and Torgerson 2008). That is, the treatment and control groups should be very similar in terms of observable and unobservable characteristics. Provided that there are no spill-over effects (from the treated group to the control group), then the observed differences between treatment and control following the intervention represent the ‘impact’ of the intervention.

In this RCT, students in the first semesters of 2013 and 2014 who were identified as being at high risk of failure were first stratified into three groups by the predicted probability of failure. Stratification was used to ensure that the treatment and control groups would be balanced in terms of their predicted probability of failure. This was necessary because of the relatively small sample size. Then, equal numbers from each stratum were randomly assigned into one of three groups:

- (1) **A control Group** which did not receive any intervention;
- (2) **Treatment Group A**, whose intervention was an email to alert them that the Department of Economics was concerned about their performance and alerting them to available support services provided by the department and the university (see Appendix for the text of this email); and
- (3) **Treatment Group B**, who received the same email as Treatment Group A, but also a follow-up personal telephone call. In the 2013 sub-sample, the follow-up telephone call was made by a staff member. A student tutor made the call in 2014. The slight difference in intervention between 2013 and 2014 allows us to additionally test whether students are more responsive to personal contact from staff, or from senior students who are closer to their own age and may therefore better understand their experiences and frustrations. In some cases, multiple attempts were required before students could be reached via telephone. No further direct intervention was provided after the initial email and telephone call.

4. Evaluation Method

We consider two outcome variables, both being measures of students' academic performance in the course: (1) a binary outcome variable (*Pass*) set to one if the student passed the course (and zero otherwise); and (2) the percentage final mark (*FinalMark*) achieved by the student. The effect of the two treatment interventions (compared with the control group) were tested using the following multiple regression equation:

$$\begin{aligned} \text{Outcome} = & \beta_0 + \beta_1 \text{Year} + \beta_2 \text{TreatmentA} + \beta_3 \text{TreatmentB} + \beta_4 (\text{Year} * \text{TreatmentA}) \\ & + \beta_5 (\text{Year} * \text{TreatmentB}) + \beta_6 X + \varepsilon \end{aligned} \quad (1)$$

Where *Outcome* is the outcome variable (*Pass* or *FinalMark*), *Year* is a dummy variable (set to one for 2014), *TreatmentA* and *TreatmentB* are indicator dummy variables for Treatment Group A and Treatment Group B respectively (the Control group is the comparator), *X* is a vector of demographic and other control variables, and ε is an idiosyncratic error term. The vector of demographic and other control variables included gender (set to one for male students), ethnicity (a dummy variable set to one for students of Asian, or New Zealand European ethnicity, and set to zero for students of Māori, Pacific Island, or 'Other' ethnicity), age group (18-20; 21-25; 26 years and over), domestic status (set to one for domestic students, and zero for international students), and decile rating of each student's previous high school as a measure of socioeconomic status. New Zealand schools are rated to indicate the extent to which they draw students from low socio-economic communities, with decile 1 representing the 'poorest' 10 percent of schools, while decile 10 represents the 'richest' 10 percent of schools. High school decile rating is only available for students who completed high school in New Zealand, so we estimate models with and without this variable included.

Outcome variable *Pass* was evaluated using a multiple logistic regression model, while *FinalMark* was evaluated using OLS regression. The variables of relevance to whether the intervention has any impact on students' academic performance are the Treatment variables, and their interactions with the Year dummy variable. Specifically, the regression model framework in Equation (1) allows us to test whether each treatment had any effect in each year. If β_2 is large, positive and statistically significant, then Treatment A had a significant impact on student academic performance in 2013. Similarly, β_3 reveals whether Treatment B had a significant impact on student academic performance in 2013. For 2014, $(\beta_2 + \beta_4)$ and $(\beta_3 + \beta_5)$ reveal the effect in that year of Treatments A and B, respectively. Additionally, the coefficient β_5 will reveal any difference in treatment between having a staff member or a senior student contact the at-risk students. Given that Treatment A was the same in both years, we expect that the coefficient β_4 will be statistically insignificant. Finally, we test whether the treatments had any effect in each year individually (which naturally omits the *Year* variable and the interaction terms).

5. Results

Table 1 shows the logistic regression model (with course failure as the dependent variable), based on 330 students enrolled in the introductory economics course in 2012. This model was used to predict students' risk of failure in 2013 and 2014 and identify potential candidates for the intervention. The model was based on limited programme of study data and course-specific behavioural data available to lecturers by the end of the fourth week of the semester. Results from the model show that students who were not management students were significantly more likely to fail in 2012, having more than double the odds of failure compared with management students. The most important predictor appears to be those who did not complete the third online test (which was due at the end of the fourth week of the semester), who had more than five times higher odds of failure than students who completed the test. This probably reflects that, by the end of the third week, students are relatively settled into the study routine, and those that are not completing assessments and coursework by that stage are likely to be at serious risk of failure. Other variables were generally not statistically significant at conventional levels, probably due to the degree of multicollinearity present in the model. However, all variables were retained in the model for prediction purposes.

Table 1. Logistic Regression Model of Failure Based on 2012 Data

Variable	Odds Ratio (Standard error)
International student	0.929 (0.299)
Non-management student	2.218** (0.735)
Not signed up for tutorials	0.329 (0.394)
Did not attend first tutorial	1.294 (0.678)
Did not attend second tutorial	2.118 (0.998)
Did not attend third tutorial	0.948 (0.508)
Not signed up for online tests	0.204* (0.186)
Did not attempt first online test	0.781 (0.488)
Did not attempt second online test	1.110 (0.558)
Did not attempt third online test	5.445*** (2.431)
Did not complete economic literacy test	2.315* (1.064)

N=330; Pseudo R² = 0.124; *** p<0.01; ** p<0.05; * p<0.1

Predicting students at high-risk of failure requires a delicate balancing act between avoiding Type I errors (incorrectly identifying a student who will not eventually fail as being high risk) and Type II errors (failing to identify a student who is high risk). Having a large number of Type I errors (low sensitivity) will lead to too many students being contacted who would not need the intervention. Having a large number of Type II errors (low specificity) would lead to students who need the intervention not being contacted at all. Predicted probabilities of failure were estimated based on the model in Table 1. We then selected a cut-off for 'high risk' that replicated as closely as possible the actual number of failing students. The resulting cut-off predicted probability of failure of 26% led to an in-sample sensitivity

(true positive rate) of 48.7% and specificity (true negative rate) of 86.7%, which are acceptable given the sample size of 330 and the goals of the intervention trial.¹

Using this model, a total of 92 students were initially selected for inclusion in the intervention: 45 (from a total of 317 enrolled students) in 2013; and 47 (from a total of 307 enrolled students) in 2014. Table 2 shows the distribution of the total sample by gender, ethnicity and domestic status. The distributions in Table 2 show that there were similar proportions of students by gender, ethnicity, and domestic status in each year of the sample. Table 3 shows the distribution of the sample by experimental group (Control, Treatment A, and Treatment B). Slightly over a third of the sample, 35%, were in the control group, while the two treatment groups had approximately 33% of students each. The experimental groups were relatively well balanced by these characteristics, with no statistically significant differences between the groups on any of these characteristics.²

Table 2. Selected Sample Descriptive Statistics

Year	Gender		Ethnicity		Origin		Total
	Male	Female	MPO	EA	Domestic	International	
2013	25	20	15	30	39	6	45
2014	22	25	19	28	39	8	47
Total	47	45	34	58	78	14	92

MPO = Maori, Pacific Island or Other ethnicity; EA = NZ European or Asian

Table 3. Treatment Group Allocation by Year, Gender, Ethnic Grouping and Student Origin

Experimental Group	Control	Treatment A	Treatment B	Total
Year	2013	15	15	45
	2014	17	15	47
Gender	Male	15	15	47
	Female	17	15	45
Ethnicity	MPO	15	10	34
	EA	17	20	58
Origin	Domestic	25	26	78
	International	7	4	14
Total	32	29	29	92

MPO = Maori, Pacific Island or Other ethnicity; EA = NZ European or Asian

Of the 92 students in the sample, 46 passed the course and 44 failed, while two students in 2014 (one each from Treatment Group B, and the Control group) made late withdrawals from the course. This reduces the overall sample size in the remaining tables below to 90. By experimental group, in 2013 8 out of 15 (53.3%) from the control group passed the course, compared with 10 out of 15 (66.7%) from Treatment Group A, and 7 out of 15 (46.7%) from Treatment Group B. In 2014, 5 out of 16 (31.3%) from the control group

¹ These results, alongside those for alternative cut-offs, are available from the authors on request.

² Results available from the authors on request.

passed the course, compared with 7 out of 15 (46.7%) from Treatment Group A, and 9 out of 14 (64.3%) from Treatment Group B.

Table 4 shows the logistic regression results (with *Pass* as dependent variable) separately for 2013 and 2014. The first and third columns include all students, while the second and fourth columns include students' high school decile rating as an explanatory variable, reducing the sample size to the number of domestic students in the sample. In 2013, Treatment A appears to increase the odds of students passing the course, while Treatment B decreases the odds of passing the course. However, these results are not statistically significant.

The results for 2014 are quite different. Both treatments appear to increase the odds of students passing the course, and the effect of Treatment B is statistically significant. Specifically, the results show that students who are part of the Treatment B group in 2014 had more than seven times higher odds of passing than the control group. Overall, we cannot definitively conclude from these sub-samples whether Treatment A increases the odds of students passing the paper compared to students in the control group, although the insignificance of results for Treatment A may be due to a lack of statistical power arising from the relatively small sample size. In contrast, the results for Treatment B (at least in 2014) are promising.

Table 4. Logistic Regression Results for Passing the Course, by Year

Regressors [†]	2013		2014	
	Odds Ratio (Standard error)	Odds Ratio (Standard error)	Odds Ratio (Standard error)	Odds Ratio (Standard error)
	(1)	(2)	(3)	(4)
TreatmentA	1.064 (1.008)	1.140 (1.416)	2.130 (1.715)	2.088 (1.969)
	0.655 (0.597)	0.426 (0.478)	8.298** (7.886)	7.630** (7.727)
N	45	38	45	36
Pseudo R ²	0.261	0.331	0.111	0.115

[†] Control variables not shown for brevity; ** p<0.05.

The results for the corresponding linear regressions on students' percentage overall mark (*FinalMark*) are shown in Table 5. These results suggest that for 2013 being in either treatment group actually slightly reduced a student's final mark on average compared to students in the control group. However, those results are statistically insignificant. In 2014, students in both treatment groups have higher marks, as indicated by the positive coefficients. The coefficients for Treatment A are statistically insignificant, but the coefficients for Treatment B are statistically significant and suggest that students in Treatment B received marks that were, on average, 20 percentage points higher than the control group (or 23 percentage points higher when controlling for high school decile rating for domestic students only).

Table 5. Linear Regression Results for Final Mark by Year

Regressors [†]	2013		2014	
	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
	(1)	(2)	(3)	(4)
TreatmentA	-1.831 (7.442)	-2.561 (9.469)	11.01 (8.061)	9.789 (10.10)
TreatmentB	-3.343 (7.045)	-6.076 (8.362)	20.30** (8.881)	23.37** (10.05)
N	45	38	45	36
Adjusted R ²	0.020	0.024	0.034	0.042

[†] Control variables not shown for brevity; ** p<0.05.

It is very likely that the results shown in Tables 4 and 5 have been affected by the relatively small samples sizes when the years are treated independently of each other. These small sample sizes reduce the statistical power to identify the effects of treatment. In contrast, Table 6 shows the results when the two years are combined into a single sample, using the model specified in Equation (1). The first two columns show the logistic regression results for the *Pass* outcome variable, with and without high school decile rating as a control variable. The last two columns show the corresponding linear regression results for the *FinalMark* outcome variable. The logistic regression results are similar to those reported in Table 4, suggesting that Treatment A increased the odds of passing the course in 2013 while Treatment B decreased the odds of passing the course. However, both effects were statistically insignificant. The effects of treatments in 2014 can be assessed by looking at the combined coefficients (the natural log of the odds ratios reported in Table 6) for the treatment variable and the interaction with the year dummy. The combined odds ratios suggest that in 2014 Treatment A increased the odds of passing the course by 93% (or 130% when controlling for high school decile rating), while Treatment B increased the odds of passing the course by 267% (or 182% when controlling for high school decile rating). However, despite the large size of the effects neither effect is statistically significant.

Table 6. Logistic and Linear Regression Results for the Combined Dataset

Regressors [†]	Logistic model, Odds-ratios(SE)		Linear model, Coefficients(SE)	
	(1)	(2)	(3)	(4)
TreatmentA	1.535 (1.222)	1.976 (1.829)	-0.457 (7.720)	-0.811 (9.256)
TreatmentB	0.734 (0.560)	0.602 (0.517)	-3.525 (7.524)	-6.483 (8.806)
Year2	0.352 (0.278)	0.393 (0.347)	-14.57* (7.509)	-16.98* (8.82)
Year2*TreatmentA	1.257 (1.399)	1.163 (1.518)	11.77 (10.70)	13.09 (13.10)
Year2*TreatmentB	5.001 (5.618)	4.689 (5.759)	19.60* (10.85)	23.58* (12.53)
Pseudo R ² / Adjusted R ²	0.082	0.097	0.039	0.034
N	90	74	90	74

[†] Control variables not shown for brevity; * p<0.1

The linear regression results are similar to those reported in Table 5. Students participating in the study achieved 14.6 percentage points lower final marks in 2014 compared with 2013 (or 17.0 percentage points lower after controlling for high school decile rating). Both treatments have small, negative, but statistically insignificant effects on student marks in 2013. Again, the effects of treatments in 2014 can be assessed by looking at the combined coefficients for the treatment variable and the interaction with the year dummy. The combined coefficients show that Treatment A increased students' final marks in 2014 by 11.3 percentage points (or 12.3 percentage points when controlling for high school decile rating), while Treatment B increased students' final marks in 2014 by 16.1 percentage points (or 17.1 percentage points when controlling for high school decile rating). The effect of Treatment A in 2014 was not statistically significant ($p = 0.13$ and $p = 0.19$ with and without the control for high school decile rating respectively), but the effect of Treatment B in 2014 was statistically significant ($p = 0.04$ and $p = 0.06$ with and without the control for high school decile rating respectively). Importantly, the linear regression results are consistent with those of the logistic regressions. The largest effects are for Treatment B in 2014, and a substantial increase in the odds of passing the course (from the logistic regression models) is consistent with a substantial increase in final marks.

6. Discussion

Interpreting the results from Tables 5 and 6 with respect to Equation (1), β_2 and β_3 (the effects of Treatment A and Treatment B, respectively, in 2013) are not statistically significant. Similarly, $[\beta_2 + \beta_4]$ (the effect of Treatment A in 2014) is also not statistically significant. However, $[\beta_3 + \beta_5]$ (the effect of Treatment B in 2014) is large, positive and statistically significant (in terms of its effect on students' final marks, if not their odds of passing the course). This reveals that Treatment B significantly improved student outcomes in 2014. The coefficient β_5 is statistically significant and positive, which suggests that the success of Treatment B in 2014, and not in 2013, arises when a senior student, rather than an academic staff member, contacts the at-risk students.

This latter result is interesting. We had initially expected, based on the literature on student engagement and retention outlined in the introduction, that developing a relationship between the lecturer and the students was most important. Instead we found that the students have responded more positively to contact from a senior student. This may be because the senior student is better able to relate to the sense of alienation or culture shock that the 'newer' students are experiencing, having recently gone through a similar experience themselves. A senior student may have more relevant advice for new students, as they may be more aware of the intricacies of dealing with university support services than academic staff, who typically have no direct experience of these systems. Moreover, new students who are feeling alienated by the university system may be more accepting of advice from someone who has been in a similar position before, providing advice that might be perceived as being more authentic.

Given the results in the previous section, it is reasonable to ask: 'What would have been the effect if Treatment B had been made available to all at-risk students in 2014?' To answer this question, we use the results from the linear regression (Column 3 in Table 6), and assume that all students in the control group receive the additional 16.1 percentage points in final marks (being the estimated effect of Treatment B, when compared with the control in 2014), while the students in Treatment Group A receive an additional 4.8 percentage points (being the difference between the effects of Treatment B and Treatment A in 2014). We compare this with the results that would have obtained assuming that all students were in the control group, which we estimate by reducing the percentage final mark of Treatment A students by 11.3 percentage points (the estimated effect of Treatment A in 2014), and the percentage final mark of Treatment B students by 16.1 percentage points (the estimated effect of Treatment B in 2014). This simple simulation demonstrates a substantial effect of Treatment B. Without the full intervention, we estimate that 13 out of 45 students would fail the course, but with the full intervention this more than doubles to 27 out of 45. In other words, the intervention would increase pass rates by around 31 percentage points.

One final consideration is the cost-effectiveness of this intervention. The proactive pastoral care initiative we trialled (Treatment B) was very simple, involving a single email (which involves minimal cost), plus follow-up phone calls. Some students required multiple follow-up calls, but in total it took no more than 12 hours to contact and advise the 14 students in Treatment B. Considering the cost of a senior student (as used in 2014) at around NZ\$25 per hour, the cost-per-student-contacted of the intervention was approximately NZ\$21. If 31 percent of those treated pass rather than fail (as per the simulation in the previous paragraph), then the cost-per-failure-averted is about NZ\$69. This seems like a reasonable cost for institutions looking to increase the pass rates in introductory courses. Of course, this cost would be greater if a lecturer is making the calls rather than a senior student, although our results suggest that the intervention works best when a senior student is the one contacting students.

Based on the results of this trial, the potential gains from a wider roll-out are substantial. However, the results need to be considered in context. The intervention was trialled in a single first-year university course. Students who were in the treated group (Treatment B) benefited from significantly increased final marks in this course in 2014. However, we have not considered the effects this may have had on other courses. It is possible that students who feel more valued in their first-year economics course put more effort into that course. However, students face competing demands for their time that affect their motivation (Winn 2002), and more effort on first-year economics may mean that these students put less effort into their other courses, for no net overall gain in their academic performance.

Alternatively, making students feel valued might create a 'halo effect' for the whole institution, whereby students feel valued not just in the first-year economics course but in their degree programme as a whole, leading to more effort across all courses and improved

academic performance as a result. We have not evaluated these impacts on students' performance in other courses or their programme of study as a whole, and so we are unable to tease out which, if any, of these negative or positive spill-over effects is apparent. Further research should address this open question.

Hand and Bryson (2008) argue that a wider institutional-level approach is needed to improve engagement for both students and staff. We concur. The cost of the initiative we implemented was small, which suggests that institution-wide rollout is achievable at relatively low-cost. A further argument for rolling out the initiative institution-wide is that the sample size in this trial was necessarily small, and so the evaluation lacked power to identify small impacts (such as the impact of Treatment A). A wider rollout would enable additional data to be collected and the initiative to be evaluated using a larger dataset, as well as testing for the cross-course effects discussed in the previous paragraph.

One area of concern may be that students respond to the proactive pastoral care initiative by adopting surface strategies, rather than deep learning. Nystrand and Gamoran (1991) distinguish between procedural engagement, which is superficial and task-based, and substantive engagement, which is a more invested, deeper level of engagement. We argue that procedural engagement is probably better for the student, and certainly better for student retention, than no engagement at all, which is the alternative for many of the students in this intervention. Students who are not at all engaged have little or no likelihood of moving to deeper learning as they progress through their studies, if they progress at all.

Finally, we must note some further limitations to our study. First, our results are based on a single course undertaken at a single institution. They may not generalise to other contexts. Further evaluations of similar low-cost interventions should be undertaken to better understand the wider applicability of this approach. However, Kahu (2013) cautions against over-generalisation and highlights the need for student engagement research that focuses on single institutions and our paper contributes in that vein.

Secondly, the difference between an academic staff member and a senior student contacting the at-risk students was evaluated across two different semesters. As our evaluation was based on a stratified randomisation within semesters, we cannot control for any other differences between those semesters that might explain the differences we found.

Thirdly, one could argue that our results represent simply a 'Hawthorne effect' (Lowis and Castley 2008). However, this should not be a concern as the particular mechanism through which students respond is less relevant than the improvement in academic performance that results from the intervention. This is the case provided, as noted above, that overall academic performance is not detrimentally affected.

7. Conclusions

In this paper we evaluated the impact of a proactive pastoral care initiative in a single first-year university course. The initiative involved a simple contact with students, making them feel welcome in the course and intending to increase student engagement. The initiative was a qualified success. When students are contacted both via email and personal telephone call, their final marks in the course are significantly higher. The initiative is simple and cost-effective, and should be rolled out across the institution, and trialled and evaluated in other institutions as well.

Appendix

Dear *****

We have identified a number of students who are at high risk of not passing ECON100, and we are concerned about your progress. Our records show that in the first four teaching weeks you have [**attended none of the three ECON100 tutorials. You have also completed just two of the Aplia online tests. You also missed the economic literacy test in the first week of the paper**].

If you are finding it difficult to keep up with the paper, there are several options for extra assistance: Student Learning Support (in the ITS building or email slsadmin@waikato.ac.nz) or the Management Student Centre (msc@mngt.waikato.ac.nz) can help you develop your time management and other study skills. If you are having particular problems with Aplia or the paper in general, you can meet with ***** or ***** during our office hours, or at any other time if you make an appointment.

We strongly recommend that you attend all your tutorials. Tutorial questions are mostly made up of past test and exam questions, and we often ask similar questions in those assessments. Tutorials also provide you with an opportunity to ask questions and receive guidance about the paper material from an experienced tutor.

Tutorial attendance is strongly linked to pass rates. While over 90% of students who attend 8 or more tutorials during the semester pass the paper, around 50% of students who attend 7 or fewer tutorials pass. Passing ECON100 is not only important for your degree programme, but as the university is more strictly enforcing the re-entry criteria it is important to pass your papers to avoid being denied re-entry next year.

If the tutorial time no longer suits your timetable, please come and see me about it and we can try to find an alternative for you. Finally, please remember that you have a test next week, and you will need to spend extra time to prepare for it.

Kind regards

***** and *****

Your ECON100 lecturers

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