Predicting Performance in an Introductory Agricultural Finance Course

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Abstract

Student performance in an introductory agricultural finance class was analyzed via a pre-test, post-test, and additional student information collected from 2018-2021. Regression analysis indicated that several common measures of academic performance and aptitude were linked to post-test scores. As is consistent with the literature, post-test score was positively related to pre-test score and grade point average and, for males, to college-entry standardized test score. Somewhat surprisingly, students that had previously taken an agricultural management class and students interested in an agricultural lending career performed worse than other students. First generation college students performed better on the post-test although this was largely tempered for male first generation students.

Keywords: assessment, agriculture, finance, performance

An instructor begins with the general assumption that students enrolled in his or her class can succeed. Instructor success in helping students do so naturally depends on what the instructor can influence such as instructional design, what the instructor cannot influence but can account for in instructional design (e.g., gender), and what the instructor generally cannot recognize (e.g., student self-efficacy). Some may argue that, if an instructor gets to know students well, there may be few performance-influencing factors in the latter category, what the instructor cannot recognize. Adoption of progressive and innovative instructional techniques should also minimize the population in a fourth category, that which the instructor can recognize but cannot account for in instructional design.

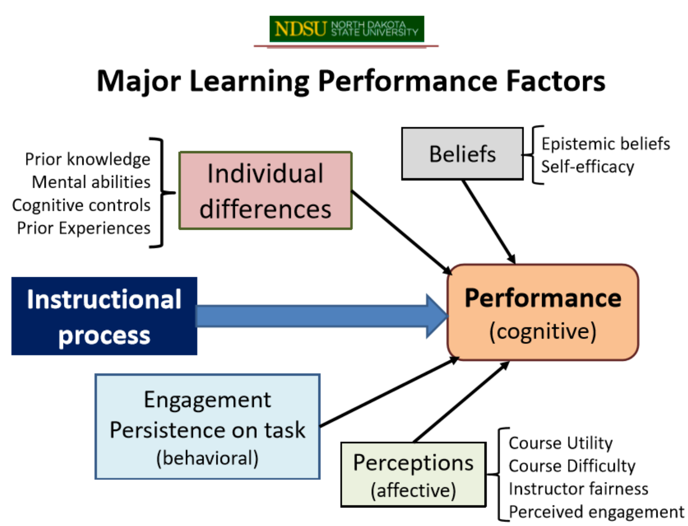
The objective of this paper is to identify among an introductory agricultural finance course those factors comprising the second category, what the instructor cannot influence but can be accounted for in curricular or instructional design. This is a natural first step in planning and implementing instructional techniques that lead to student success. We do so by estimating the effects of student characteristics, experiences, and other factors on an end-of-term assessment.

Factors Affecting Performance

As adopted from Cernusca (2019) and supported by Walsh and Robinson-Kurpius (2016) and others, student performance can be influenced by the instructional environment and process; individual differences including academic aptitude, prior experiences, and demographics; personality and perceptions about self (e.g., self-efficacy, confidence); student interest in the class; and student behavior (e.g., study hours, attendance) (figure 1).

Figure 1.

Factors Influencing Academic Performance



Note. From Cernusca, Dan. Scholarship of Teaching and Learning: Creating Synergy Between Teaching and Educational Research. CAFSNR Teaching Café, September 20, 2019. Used with permission.

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There is a wide body of literature that investigates this myriad of factors that affect student performance in a specific course, on a standardized test, or more generally in a student's academic career. Identified predictive factors include academic performance; previous classes; interest and other attitudinal and psychological factors; demographics (e.g., race, ethnicity, socioeconomic status, age, gender, work experience, and first-generation college student); student workload; and previous work or related experience.

In general, the literature identifies demonstrated academic ability (e.g., grade point average) as an important predictor of performance and this predictive ability is consistently significant and positive across most studies (Yousef 2019; Kader 2018; Payne and O'Malley 2017; Thiele et al. 2016; Walsh and Robinson-Kurpius 2016; Koh 2014; Thammasiri et al. 2014; Al-Twaijry 2010; Grover, Heck and Heck 2010; Allen et al. 2008; Johnson and Kuennen 2006; Choudhury, Robinson, & Radhakrishnan, 2007; and Garton, Ball and Dyer 2002). Standardized tests, long used to evaluate candidates for college admissions, have also been associated with subsequent academic performance (Garton, Ball and Dyer 2002).

The literature is, however, mixed on the predictive power of grades in or completion of previous courses (e.g., Shoulders et al. 2018; Wei and Burrows 2016; Biktimirov and Armstrong 2015; Ritchie et al. 2011; Al-Twaijry 2010; Guney 2009; and Tan and Laswad 2008). Specific to performance in introductory finance classes, previous work shows better performance when a student has completed coursework in math, financial accounting and economics (Payne and O'Malley 2017; Grover, Heck and Heck 2010; Marcal and Roberts 2001; and Borde et al. 1998).

Factors related to the third category, what the instructor generally cannot recognize (e.g., student self-efficacy), have also been investigated in the literature, including intrapersonal factors and student interest. Interpersonal factors identified in the literature include: self-motivation (Youp and Suki 2019); self-efficacy or confidence in one's abilities and skills (Walsh and Robinson-Kurpius 2016; Huff et al. 2016; Schunk 2016); goal orientation (Huff et al. 2016; Schunk 2016; Koh 2014); learning style and environmental factors (Huff et al. 2016); and personality (Nishii, Arai and Seno 2012). Student interest in the subject and career intent in the field have been shown to be directly related to performance in a course (Cromley, Perez and Kaplan 2016; Guney 2009).

The effect of sociodemographic factors on academic performance have been investigated. Factors include race, age, gender, first generation college student status, and work experience. The effect of working hours has also been studied. Race and age are often excluded as is the case here because the population considered is relatively homogeneous in each attribute. The literature is inconclusive regarding the effect of gender on performance. No effect was identified by Guney (2009), Grover, Heck and Heck (2010), Yousef (2019), and Soyer and Kirikkanat (2019). Thiele et al. (2016) found women at a British university outperformed men. Johnson and Kuennen (2006) reported women earned a higher grade in an introductory business statistics course, and the interaction between gender and professor was significant, indicating the gender effect may differ by instructor or pedagogy. Vella, Turesky and Hebert (2016) reported female students performed better in online courses, but the advantage dissipated with age. Contrary to other literature investigated, Kader (2018) found males to perform better in an introductory economics course. The advantage did not exist when psychological factors were included in the estimation.

The effect of first-generation college student status is also inconclusive. Pike and Kuh (2005) found that first generation students did not perform as well as their counterparts. They attributed this to a lower level of engagement, perception of less support and making less intellectual progress (self-reported). Soyer and Kirikkanat (2019) and Walsh and Robinson-Kurpius (2016) did not find differences between first generation students and their counterparts. And, finally, there is some support from the literature that those with previous work experience perform better than their counterparts in accounting courses (Koh 2014; Guney 2009) although there is no clear consensus about the relationship between work hours and academic performance (Payne and O'Malley 2017).

Overall, the literature on performance in courses and on assessments demonstrates that there are many potential influencers and that the predictive power of estimation of performance can be improved when exogeneous variables are included (Cosgrove and Olitsky 2015; Biktimrov and Armstrong 2015; and Guney 2009). This review also suggests that selecting a predictive model can have an important effect on the outcome and, in particular, it is important to consider relationships between explanatory variables (e.g., those correlated). For example, Shoulders et al. (2018) found the otherwise significant effect of grade point average in prerequisites including biology, chemistry and statistics in predicting performance in food chemistry was no longer significant when overall student grade point average was included as an independent variable. This paper adopts the learning factors influencing performance model introduced in figure 1. Model design and analysis were framed so as to mitigate effects of correlation between variables and consider, when appropriate, inclusion of interaction variables.

Methods

A financial assessment and survey were administered to students as both a pre- and post-test over four years (2018-2021) in AGEC 246, the introductory class in the North Dakota State University (NDSU) Department of Agribusiness and Applied Economics Department agricultural finance sequence. Pre-tests allow for the identification and assessment of students' incoming level of knowledge (Custers 2010). Instructors can therefore devote additional resources towards areas where students need additional help and fewer resources on concepts they have largely mastered (Heinfeldt and Wolf 2002; Grover, Heck and Heck 2010; and Payne and O'Malley 2017). Administration of pre-tests has also been demonstrated to facilitate learning, such as during subsequent study (Arnold and McDermott 2013; Szpunar, Khan and Schacter 2013; Bjork, Soderstrom and Little 2015; Little and Bjork 2016; Payne and O'Malley 2017; and Yue, Soderstrom, and Bjork 2015).

Data Collection

All students voluntarily participated in this project, which was identified as exempt by the NDSU Institutional Research Board (protocol #AG19077). AGEC 246 is designed as a lecture course with in-class problem solving and prescribed opportunities for student-to-student interaction. A response system technology is employed. The course provides students with a background in agribusiness credit use and evaluation for farms, ranches, and other agribusinesses. Topical areas are time value of money; cost of financial capital; capital budgeting methods and investment analysis; financial analysis, planning and control including financial statements and ratio analysis; and capital structure, leverage, and risk management. The course is required for agribusiness and agricultural economics majors, and is also part of the required or suggested coursework for several other majors and minors in the College of Agriculture, Food Systems, and Natural Resources. There are no prescribed prerequisites. The same instructor taught the course throughout the study.

Participating students were asked about their course history, specifically whether they had taken a college-level introductory farm management or accounting course. Similar information was provided by the NDSU Office of Institutional Research and Analysis (OIRA). The OIRA also provided the following information that was collected upon students' entry to NDSU: gender; age; hometown; first generation college student status; ACT composite score and sub-scores; high school class rank, percentile, and GPA; transfer credits and source (high school versus post-secondary); and transfer credit equivalents. Finally, the OIRA provided the following information describing students' experiences at NDSU: entry term; GPA; major; and minor.

In the survey, students were asked about their background, including where they grew up (farm or ranch, rural area, urban area) and their experience with farming and ranching, generally, along with their experience with specific agricultural enterprises. Students were also asked Likert scale questions asking them to rate their level of agreement with statements such as: "I will apply for a position in agricultural lending within five years of college graduation" and "I will be actively farming or working as a farm manager within five years of college graduation."

In the financial assessment, students were asked twenty-five questions to assess their financial competency. Possible score range was from 0 to 25. Subject areas included time value of money (five questions), capital budgeting (two), financial statements (five), financial ratios (six), cost of capital (two), and lending (five).

Model

Ordinary least squares regression was used to analyze post-test scores. Post-test scores were regressed on several variables hypothesized to influence performance on the assessment: a binary variable equal to one for a student that was assessed in 2018; a binary variable equal to one for a student that was assessed in 2019; a binary variable equal to one for a student that had previously taken an agricultural management class; a binary variable equal to one for a male student; a student's college GPA; a student's pre-test score on the same assessment; a student's composite ACT score; an interaction variable multiplying the male variable and ACT score (thereby modeling differential effects for male students); a binary variable equal to one for a first generation student; an interaction variable multiplying the male variable and first generation student binary variable (thereby modeling differential effects for male students); a student's rating of their intent to pursue a career in agricultural lending; and a binary variable equal to one for a student majoring in agribusiness or agricultural economics. Table 1 contains summary statistics for post-test scores and the explanatory variables included in the regression model.

The regression model was estimated for the 324 students that had complete data for all variables used in the model. This is 71.7% of the 452 students that took a pre-test or post-test in the class at some point from 2018-2021. Table 1 shows that the average assessment score increased from the 11.68 on the pre-test to 13.99 on the post-test (p=0.00 based Student's t-test). Other factors related to post-test scores are analyzed in the following section.

Results and Discussion

Several of the explanatory variables described in Table 1 have a strong association with post-test scores. Table 2 shows that post-test score is positively correlated with college grade point average (p=0.00), pre-test score (p=0.00), and ACT score (p=0.00). These results are unsurprising and align with much of the existing literature. In contrast, post-test score is negatively correlated with students' lending intent (p=0.00), which is a surprising result indicating that students' careers motivations do not necessarily create better academic performance.

Table 3 contains ordinary least squares regression results for the model predicting post-test score. The model has an R2 of 0.480 and an adjusted R2 of 0.460. The regression results provide several interesting insights that build on the relationships visible in Table 2.

Regression results indicate that post-test scores were lower for students that took the class in 2018 (p=0.01) and higher for students that took the class in 2019 (p=0.00). The coefficients attached to these variables offer a comparison to baseline years of 2020 and 2021. In 2020 and 2021, students took the assessment in similar formats (online) and received some or all of their instruction online due to the COVID-19 pandemic. The negative coefficient for 2018 may reflect the limited study assistance received that year, while the positive coefficient for 2019 may reflect better preparation by students because the post-test in 2019 was embedded within the final exam. As such, students were motivated to review material prior and had a stake in the accuracy of their answers. These results agree with the instructor's impressions of performance on the assessment

Table 1.

Summary Statistics for Model Variables

Variable	Mean	Standard deviation	Minimum	Maximum
Post-test score	13.99	3.70	3	22
2018 cohort	0.38	0.49	0	1
2019 cohort	0.19	0.39	0	1
Previous management class	0.69	0.47	0	1
Male	0.73	0.44	0	1
GPA	3.13	0.60	1.24	4
Pre-test score	11.68	3.00	4	21
ACT	23.02	3.59	13	33
ACT x Male	16.49	10.62	0	33
First generation student	0.08	0.27	0	1
First generation student x Male	0.05	0.21	0	1
Lending career intent	3.01	1.15	1	5
Agribus. or ag. econ. major	0.53	0.50	0	1

in 2018 and 2019.

Students that had previously taken an agricultural management class performed worse on the post-test than other students (p=0.02). An agricultural management class typically covers topics assessed on the post-test, so this negative coefficient may seem somewhat surprising. However, because pre-test score is also included as an explanatory variable, the negative coefficient attached to the previous agricultural management class variable may indicate that these students had less room to improve their performance from pre-test to post-test because they were already relatively familiar with the subject matter. Indeed, students that had previously taken an agricultural management class achieved higher pre-test scores than other students (11.91 vs 11.13, p=0.02). More generally, this is a reminder that students in a class do not improve uniformly, and instructors should remember that previous experiences may influence the progress made during the semester.

Table 2.

Correlation Coefficients Between Explanatory Variables and Post-Test Scores

Variables	Post-test score
2018 cohort	-0.339***
2019 cohort	0.380***
Previous management class	-0.002
Male	-0.058
GPA	0.348***
Pre-test score	0.432***
ACT	0.411***
First generation student	0.002
Lending career intent	-0.165***
Agribus or ag. econ. major	0.030

Gender was significant in predicting performance and, as is consistent with much of the literature, there was a relatively large negative coefficient on the male variable. However, although the size and significance of this coefficient suggest that male students did much worse than female students, the mean of post-test scores for female students was only 0.46 points better than male students (14.32 versus 13.86, p=0.13). Furthermore, when expected post-test scores are calculated using the regressions coefficients and the mean values of explanatory variables, the difference between males and females is just 0.08. Therefore, the coefficient for the male variable isn't important on its own and is instead dampened substantially by the effect of interaction terms including Male (ACT x Male and First-generation student x Male) which are also included in the model.

As expected, measures of academic performance and aptitude were generally linked to post-test scores. For example, post-test scores improved with college GPA (p=0.00), which offers evidence that academic history is a useful predictor of performance and learning within a class. Instructors can use this information as they plan instruction at the beginning of a semester. Likewise, students with higher pre-test scores also did better on the post-test (p=0.00), indicating that students with the best incoming knowledge of the assessed topics were also stronger at the end of the

Table 3.

Regression Results

Variable	Coefficient	Standard error	P-value
Constant	8.121	2.110	0.000
2018 cohort	-0.920	0.364	0.012
2019 cohort	3.308	0.439	0.000
Previous management class	-0.860	0.369	0.020
Male	-6.915	2.263	0.002
GPA	1.037	0.315	0.001
Pre-test Score	0.283	0.059	0.000
ACT	0.008	0.088	0.929
ACT x Male	0.297	0.097	0.002
First generation student	2.080	1.001	0.038
First generation student x Male	-1.661	1.255	0.186
Lending career intent	-0.317	0.141	0.026
Agribusiness/ag econ major	0.631	0.336	0.061
R^2		0.480	
Adjusted R^2		0.460	

semester. Finally, although ACT score is not linked with post-test performance (p=0.93), the ACT x Male interaction term has a positive relationship with post-test scores (p=0.00). This result suggests that ACT is a good indicator of improvement during the class for male students, but not as important for predicting the success of female students. This finding encourages instructors to acknowledge student differences when planning instruction.

First generation students had higher post-test scores (p=0.04), although this result is less important for male students (p=0.19). The literature shows that challenges may exist for first generation students, but that considerable nuance exists in predicting how students will overcome those challenges. In this case, female first generation students may be performing better than their male peers.

Collier and Morgan (2008) indicate that designation as a first-generation college student may affect performance when this cohort enters college with different expectations about the university and its processes and a different level of ability to meet these expectations. They suggest differences can be related to expectations regarding amount of work and assignments, and the processes of prioritizing efforts, communication, and problem solving. Working with students to align expectations more closely with experiences may lead to higher academic success.

Surprisingly, students intending to pursue a career in agricultural lending fared worse on the post-test than other students (p=0.03). This relationship may exist because of a divergence between students' career interests and their academic strengths. Furthermore, students may have an unclear view of their likely career path, particularly in an introductory class like the one assessed in this study. Regardless, instructors would be well served by intentionally connecting the course objectives with the wide range of interests and aspirations present in the class.

Summary

This study analyzed student performance in an introductory agricultural finance class from 2018-2021. Regression analysis identified several factors that were associated with scores on a post-test. As expected, common measures of academic performance and aptitude such as college grade point average and ACT score (for male students only) were generally linked to post-test scores. Students that had previously taken an agricultural management class performed worse than other students, as did students interested in an agricultural lending career. Interestingly, the predictive power of ACT differed between male and female students.

Agribusiness and agricultural economics are male-dominated majors at many colleges and universities (Lim et al., 2014). Indeed, 73 percent of students surveyed for this study are male. In this context, the different determinants of performance for male and female students are worthy of careful consideration. In promoting female enrollment and success in agribusiness and agricultural economics, awareness that different factors drive performance for male and female students is an important starting point. Although the particular results of this study may not be generalizable to all students and classrooms, the perspective adopted herein is valuable.

There are many opportunities to build on this research because many departments and instructors periodically assess their classes. This study used four separate years of data, which is a relatively long time period for analysis. However, it would be possible to extend this further to create a larger sample size. Analyzing retention of learning from one semester or longer after the initial class is another area in which analyzing a longer time period may be helpful.

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