

Original Research Articles

Student Background Information: Can It Predict Success in an Agricultural Economics Graduate Program?

A. Leann Westbrook^{1a}, Eric A. DeVuyst^{1b}, B. Wade Brorsen^{1c}¹ Oklahoma State University

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Abstract

Graduate program applicants are typically required to provide general background information, prior testing and academic history, letters of recommendation, purpose statements, and—depending on the program—an in-person interview. The primary question addressed here is what value test scores and prior grade point average (GPA) have in predicting enrolled students' success in an agricultural economics graduate program. Multiple measures of success are considered, including students' overall GPA, semesters to graduation, and GPA in core program courses. Independent variables of interest include prior program GPA, Graduate Record Exam (GRE) sub-scores, and domestic or international student status for Oklahoma State University's Department of Agricultural Economics' graduate students between 2002 and 2021. The MS regressions had considerable explanatory power, while the PhD regressions did not. For the MS program, students' prior GPA was a strong predictor of overall GPA while GRE analytical writing helped predict some MS outcomes. Even so, success is difficult to predict. The results therefore support admissions committees using a holistic approach that considers information that is difficult to quantify and include in a regression model.

1. Introduction

Graduate admissions committees evaluate applicants based on undergraduate grades, standardized test scores, letters of recommendation, personal statements, evidence of research experience, and other information. This research focuses on the two most used information sources: undergraduate grades and scores on the Graduate Record Exam (GRE). A key finding is that prior GPA is the more consistent predictor of graduate success, which suggests that admissions committees should put more weight on previous grades than on test scores.

While most graduate schools still require the GRE, many US undergraduate institutions have begun to waive standardized test score requirements such as the American College Test (ACT) and Scholastic Assessment Test (SAT). Since the fall of 2022, Oklahoma State University (OSU) has waived undergraduate test score requirements for admission into all undergraduate programs across campus. (Test scores are still required to

a A. Leann Westbrook is a PhD candidate, Department of Agricultural Economics, Oklahoma State University, Stillwater, Oklahoma.

b Eric A. DeVuyst is a Professor and H.E. Rainbolt Endowed Chair, Department of Agricultural Economics, Oklahoma State University, Stillwater, Oklahoma.

c B. Wade Brorsen (corresponding; wade.brorsen@okstate.edu) is a Regents Professor and A.J. and Susan Jacques Chair, Department of Agricultural Economics, Oklahoma State University, Stillwater, Oklahoma.

apply for scholarships and test scores can be used for admission when grades or class rank are too low to be admitted without test scores.) Each OSU graduate program can require GRE scores for program admission or waive the requirement. There are some schools—such as New Mexico State University (New Mexico State University 2023) and The University of Arizona (University of Arizona 2023)—that waive the GRE score requirement in their graduate program applications. OSU’s agricultural economics department requires the GRE, and the requirement is rarely waived.

The GRE requires individuals to pay a fee to complete the exam and make scores available to potential schools. It is a considerable financial burden to many international students. During COVID and the subsequent semesters, some OSU graduate programs waived GRE requirements. Given the pressure to not require GRE scores, the question posed here is: How valuable are GRE scores and other academic background data in measuring enrolled graduate student success? To answer this question, this research assesses the predictive power of measures of prior academic performance and GRE scores on various measures of graduate student academic success.

Our data include only students who enrolled. This can create sample selection bias (Heckman 1990). Two distinct mechanisms are relevant. First, admissions decisions generate a range restriction in GRE scores and prior GPA, which attenuates coefficients toward zero (Sackett and Yang 2000; Carretta and Ree 2023). Second, selectivity occurs when students are admitted with low grades or test scores and end up doing well when the committee had other information, such as knowing the student was working 30 hours a week as an undergraduate, was sick when taking the GRE, or had convincing recommendation letters, which are not included in our data.

While the bias from the second mechanism can be in either direction, we argue that it also most likely shrinks estimates toward zero with our data. For example, applicants with relatively low GRE scores (or low grades) are funded when other indicators suggest success, implying that, among enrolled students, these other indicators are negatively correlated with GRE scores. Further, some of the strongest applicants with both high GRE scores and other favorable indicators receive multiple offers and enroll elsewhere, removing observations from the upper tail of the joint distribution of GRE and other indicators. Because these other indicators are positively related to graduate performance, both mechanisms create negative correlation between GRE scores and the regression error term and so they bias estimated GRE coefficients toward zero. Thus, our estimates likely understate the usefulness of student background measures for admissions decisions.

2. Background

Hirschberg and Itkin (1978) wrote an early article addressing graduate student performance and found student background information to be useful in assessing student success in courses. More recently, Feldon et al. (2024)

conducted a meta-analysis of 201 studies and found that while GRE scores were insignificant in the majority of studies, the meta-analysis showed a small significant effect of GRE scores.

Within agricultural economics, Ethridge and Hudson (1996) studied GRE scores in the agricultural economics program at Texas Tech. They reported that quantitative GRE scores and previous program GPA were significant predictors of overall program GPA. They also found “financial assistance and higher than average prior GPAs were significantly related to completing a graduate program” (Ethridge and Hudson 1996, 169). Other fields interested in knowing more about the predictability of success from test scores included biomedical fields (Moneta-Koehler et al. 2017), criminal justice programs (McKee et al. 2001), and MBA programs (Wilson and Hardgrave 1995). Past studies used a variety of measures of “success.” McKee et al. (2001) and Sharon (1972) used program GPA to define success. Other studies chose publications, presentations, likelihood to pass qualifiers, or letters of recommendation to indicate success (Matthews and Martin 1992; Hirschberg and Itkin 1978). A few studied the individual’s personality, grit, and/or conscientiousness rather than test scores as a predictor of success (Duckworth et al. 2012; Duckworth and Gross 2014; and Rimfeld et al. 2016). The last two groups considering “qualitative” information assessed students’ willingness or ability to complete work rather than measures attained through test scores.

Most, if not all, past models included standard admission criteria (e.g., age, GRE scores, nationality, prior program GPA). Previous research indicated varied effects of the predictor characteristics. House and Johnson (1993) argued that since program requirements differed across universities and fields, variation across fields is unsurprising. Due to the variation across academic fields, there is a need for further work in agricultural economics. Questions about graduate admissions are especially timely as agricultural economics departments reconsider the training and skills needed to maintain the discipline’s relevance (Zilberman et al. 2025).

2.1. Hypotheses

The Department of Agricultural Economics at Oklahoma State University offers three graduate degrees: a Master of Agriculture (MAg), a Master of Science (MS), and a Doctor of Philosophy (PhD). The MAg degree is relatively small (31 students over the study period) and has flexible course requirements, so data on MAg are not included. The MS thesis option requires a thesis component covering a research topic in the field of agricultural economics approved by the student’s Academic Advisory Committee (Oklahoma State University, Department of Agricultural Economics 2019). The PhD requires passing a comprehensive exam as well as completing a dissertation.

Three hypotheses involving application information consisting of nationality, GRE sub-scores, and prior GPA are tested. Graduate program performance is measured by overall GPA, semesters to graduation, and GPA in core program courses. The hypotheses are:

1. H1: Due to less grade inflation in international undergraduate programs, international students will perform relatively better than predicted by their application information.
2. H2: GRE scores are predictive of graduate program performance.
3. H3: Prior GPA is predictive of graduate program performance.

3. Data

The research was approved by the Institutional Review Board of Oklahoma State University (#21-160-STW). Data used include background and performance information of students enrolled in the Department of Agricultural Economics at Oklahoma State University from 2002 to 2021. Information consists of GRE sub-scores for analytical, verbal, and quantitative; nationality; prior program GPA; degree programs; overall program GPA; GPA in program core courses (AGEC 5103 Mathematical Economics, STAT 4043 Applied Regression Analysis, AGECE 5213 Econometric Methods, ECON 6023 Microeconomic Theory II, AGECE 6213 Advanced Econometrics, AGECE 6103 Advanced Applications of Math Programming);¹ and semesters to graduation. The 358 students consist of 222 MS and 136 PhD students.

The Educational Testing Service (ETS) developed the GRE to measure quantitative, verbal, and analytical reasoning (Manhattan Review 2021). The analytical portion changed in 2002 to a writing portion scored from 0 to 6 (Educational Testing Service 2020). The quantitative and verbal reasoning scoring scale revision occurred in 2011 when test creators switched from scoring 200–800 to the current scale of 130–170 (Manhattan Review 2021). Older GRE quantitative and verbal sub-scores were rescaled to have the same upper and lower limits as the post 2011 possible scoring scale of 130–170.

Data variable summaries and descriptive characteristics are available in [Tables 1–4](#). [Tables 1](#) and [2](#) show the mean prior GPA; GRE analytical, verbal, and quantitative sub-scores; and the total number of students per domestic, international, or unknown domestic or international-student status respectively for the grades assigned in core courses for MS students and for PhD students, respectively. Regarding overall program GPA, [Table 3](#) displays the mean GRE scores, prior GPA, and total number of students per domestic,

¹ Mathematical Economics, Linear Regression, and Econometrics are core courses for the MS degree program.

Table 1. Variable means by MS core courses and grade assigned

Core Course	Grade Received	Number of Students ^a			MS Student Prior Grade Point Average			Graduate Record Exam Analytical Reasoning			Graduate Record Exam Verbal Reasoning			Graduate Record Exam Quantitative Reasoning		
		Nationality			Nationality			Nationality			Nationality			Nationality		
		UNK ^b	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT
Mathematical Economics																
	A	23	56	33	3.6	3.7	3.6	3.7	4.0	3.0	140.3	148.6	142.9	152.0	151.2	155.9
	B	17	31	12	3.3	3.4	3.2	3.5	3.5	3.1	144.7	147.4	138.6	152.0	148.1	152.9
	C	3	6	-	2.4	3.3	-	-	3.4	-	-	141.8	-	-	147.2	-
	Unknown	23	10	8	3.3	3.4	-	-	3.4	3.4	-	145.8	146.7	-	149.3	153.3
Linear Regression																
	A	15	63	29	3.4	3.7	3.6	3.6	3.9	3.2	141.4	147.7	141.4	152.0	150.3	153.9
	B	9	25	15	3.1	3.4	3.2	-	3.5	2.8	-	147.9	142.5	-	149.4	156.1
	C	6	4	1	3.1	3.7	3.6	-	3.8	3.0	-	154.0	141.0	-	151.0	161.0
	Unknown	39	11	8	3.4	3.4	-	-	3.6	3.3	-	145.3	145.7	-	148.9	152.6
Econometrics																
	A	19	33	21	3.6	3.7	3.6	3.5	4.2	3.0	137.6	149.9	142.7	151.3	153.1	156.8
	B	20	47	20	3.2	3.5	3.3	4.0	3.6	3.1	153.0	146.5	139.2	154.0	148.3	154.9
	C	1	1	-	3.7	3.7	-	-	3.0	-	-	149.0	-	-	154.0	-
	Unknown	26	22	12	3.3	3.7	3.9	-	3.5	3.3	-	147.4	147.1	-	149.4	150.0
Totals Mathematical Economics, Linear Regression, and Econometrics																
		66	103	53	3.4	3.6	3.5	3.6	3.8	3.1	141.4	147.7	142.4	152.0	150.0	154.7

Notes: ^aCount of students enrolled in each course by the grade they received.

^bUNK, DOM, and INT indicate unknown, domestic, and international student nationality respectively.

Table 2. Variable means by doctoral core courses and grade assigned

Core Course	Grade Received	Number of Students ^a			Doctoral Student Prior GPA			GRE Analytical Reasoning			GRE Verbal Reasoning			GRE Quantitative Reasoning		
		Nationality			Nationality			Nationality			Nationality			Nationality		
		UNK ^b	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT
Microeconomic Theory II																
	A	8	5	24	3.7	3.8	3.7	3.0	3.7	2.7	143.6	151.4	144.5	151.3	153.7	157.0
	B	11	29	34	3.4	3.7	3.7	3.5	4.0	3.1	149.3	148.8	144.4	145.3	153.6	152.2
	C	-	1	3	-	3.8	3.6	-	-	3.0	-	-	147.5	-	-	148.5
	Unknown	9	6	6	3.7	3.9	3.7	3.0	4.1	3.2	132.5	147.6	140.3	162.7	154.0	152.6
Advanced Econometrics																
	A	12	20	28	3.6	3.8	3.8	4.0	4.1	2.9	149.0	149.4	144.3	150.7	153.5	154.5
	B	5	6	28	3.2	3.6	3.6	-	3.5	3.0	-	152.2	144.5	-	154.6	152.7
	C	-	1	3	-	-	3.6	-	3.0	3.3	-	138.0	150.3	-	147.0	157.5
	Unknown	11	14	8	3.7	3.8	3.7	3.2	4.1	3.2	136.8	147.5	140.4	158.8	154.4	154.3
Advanced Mathematical Programming																
	A	12	28	47	3.7	3.8	3.7	4.0	3.8	3.0	149.0	149.1	144.8	150.7	153.7	153.7
	B	-	4	5	-	3.8	3.5	-	4.3	2.8	-	154.3	145.2	-	152.3	158.2
	C	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Unknown	16	9	15	3.5	3.8	3.7	3.2	4.1	3.0	136.8	145.6	141.1	158.8	154.0	152.1
Totals																
		28	41	67	3.6	3.8	3.7	3.5	4.0	3.0	140.8	148.8	144.2	156.1	153.6	153.8

Notes: ^aCount of students enrolled in each course by the grade they received.

^bUNK, DOM, and INT indicate unknown, domestic, and international student nationality, respectively.

international and unknown nationality for the final GPA assigned per program degrees. [Table 4](#) includes the variable means of student nationality, prior GPA, and GRE sub-scores by semesters to graduation.

4. Procedures

Previous studies primarily used linear regression models when predicting success considering GPA as a continuous dependent variable (Sharon 1972; Hirschberg and Itkin 1978; Moneta-Koehler et al. 2017; McKee et al. 2001). Alternatively, logistic or stepwise logistic regression has been used, with the limited dependent variable classifying participants as completing the program or not (Graham 1991; House and Johnson 1993). Other methods for measuring success through either continuous GPA or classification variables (i.e., first-semester grades) included canonical correlation (Abedi 1991) and

Table 3. Variable Means by Overall Grade Point Average and Grade Assigned

Overall GPA Category	Number of Students ^a			Prior GPA			GRE Analytical Reasoning			GRE Verbal Reasoning			GRE Quantitative Reasoning		
	Nationality			Nationality			Nationality			Nationality			Nationality		
	UNK ^b	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT
Master of Science															
Unknown	12	5	7	3.3	3.4	-	-	3.3	3.4	-	142.2	148.4	-	146.8	153.4
3.0–3.49	15	26	14	3.1	3.4	3.2	-	3.4	2.9	-	148.1	142.4	-	148.7	154.9
3.5–4.0	36	72	32	3.5	3.6	3.6	3.6	3.9	3.2	141.4	147.8	140.7	152.0	150.6	154.6
DNF ^c	3	-	-	-	3.2	-	-	-	-	-	-	-	-	-	-
Total	66	103	53	3.4	3.6	3.5	3.6	3.8	3.1	141.4	147.7	142.4	152.0	150.0	154.5
Doctoral															
Unknown	4	6	6	1.9	3.8	3.5	3.5	4.2	3.0	135.0	149.7	141.0	-	156.9	151.3
3.0–3.49	3	5	17	3.4	3.7	3.6	-	3.7	3.1	148.7	143.7	141.7	156.7	150.2	151.8
3.5–4.0	16	30	44	3.6	3.8	3.7	3.8	3.9	2.9	143.8	149.3	145.3	151.5	153.4	154.7
DNF	4	-	-	3.9	-	-	2.5	-	-	130.0	-	-	161.3	-	-
Withdrew	1	-	-	3.1	-	-	-	-	-	-	-	-	-	-	-
Total	28	41	67	3.6	3.8	3.7	3.5	4.0	3.0	140.8	148.8	144.2	156.1	153.6	153.8

Notes: ^aCount of students enrolled in each overall GPA category.

^bUNK, DOM, and INT indicate unknown, domestic, and international student nationality, respectively.

^cDNF indicates that a student did not finish the program.

Table 4. Variable means by semesters to graduation

Semesters	Number of Students ^a			Prior GPA			GRE Analytical Reasoning			GRE Verbal Reasoning			GRE Quantitative Reasoning		
	Nationality			Nationality			Nationality			Nationality			Nationality		
	UNK ^b	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT	UNK	DOM	INT
Master of Science															
2–5	31	66	18	3.5	3.6	3.5	3.7	3.8	3.0	143.4	147.1	140.9	152.9	150.0	153.1
6–9	12	11	14	3.0	3.5	3.3	3.5	3.9	3.3	135.3	149.9	139.2	149.3	153.2	154.0
10–14	4	5	6	3.0	2.9	3.4	-	3.0	2.8	-	142.2	137.0	-	142.4	156.7
15–22	1	-	3	3.7	-	-	-	-	2.5	-	-	141.0	-	-	158.0
DNF ^c	18	6	7	3.4	3.4	-	-	4.0	3.4	-	141.7	146.6	-	141.3	151.3
Progress	-	14	5	-	3.8	3.7	-	3.7	3.1	-	151.5	149.6	-	151.4	159.6
W	-	1	-	-	3.3	-	-	3.0	-	-	140.0	-	-	143.0	-
Total MS	66	103	53	3.4	3.6	3.5	3.6	3.8	3.1	141.4	147.7	142.4	152.0	150.0	154.5
Doctoral															
2–5	1	-	1	3.8	-	3.3	-	-	4.5	-	-	140.0	-	-	155.3
6–9	1	14	4	3.9	3.8	3.6	-	3.8	3.0	-	147.6	137.5	-	152.6	152.3
10–14	12	12	37	3.5	3.8	3.7	3.8	3.8	3.0	143.8	148.5	144.9	151.6	153.2	153.5
15–22	3	1	6	3.7	3.8	4.0	-	-	2.5	-	-	140.0	-	-	152.0
DNF ^c	9	7	9	3.7	3.8	3.6	2.5	4.0	3.1	139.3	145.6	142.3	159.0	156.0	152.7
Progress	1	7	10	-	3.8	3.8	3.5	4.3	3.0	135.0	154.5	148.4	164.0	153.7	156.5
W	1	-	-	3.1	-	-	-	-	-	-	-	-	-	-	-
Total PhD	28	41	67	3.6	3.8	3.7	3.5	4.0	3.0	140.8	148.8	144.2	156.1	153.6	153.8

Notes: The semesters include summer sessions, so six semesters would be exactly 2 years.

^aCount of students enrolled in each category.

^bUNK, DOM, and INT indicate unknown, domestic, and international student nationality, respectively.

^cDNF, Progress, and W indicate a student did not finish the program, the student is currently in the program, or the student withdrew from the program, respectively.

discriminant analysis (Wilson and Hardgrave 1995). Here, continuous and limited dependent variable regressions are used focusing on success measures including student's overall grade point average (GPA), semesters to graduation, and GPA in core courses in Oklahoma State University's (OSU) agricultural economics graduate program.

4.1. Student Success Model Selection

Student information was used to decide who was admitted into the programs by the graduate committee. Information on students not admitted was not kept² and so the possibility of selectivity bias could not be considered. In most cases, students considered for admittance and accepted into graduate programs have test scores and/or GPAs that exceed some minimal requirements. For example, the OSU Graduate College requires a minimum 3.0 GPA (out of 4.0) from prior degree programs. However, admission on probation is possible.

4.2. Overall GPA Model

A Tobit regression model (McDonald and Moffitt 1980; Greene 2018) was used for overall GPA since students cannot get above a 4.0 GPA. The model was estimated in Stata using the *tobit regression* command (StataCorp 2021). The default methods in Stata were used and so no degrees of freedom adjustments were made when calculating standard errors. Separate regressions were estimated for MS and PhD students. The latent-variable ($OvGPA_i^*$) equation for overall program GPA and the transformation to observed GPA ($OvGPA_i$) are

$$\begin{aligned} OvGPA_i^* &= \beta_0 + \beta_1 AGRE_i + \beta_2 VGRE_i + \beta_3 QGRE_i \\ &\quad + \beta_4 PriorGPA_i + \beta_5 DOI_i + e_{1i}, \\ OvGPA_i &= \begin{cases} OvGPA_i^*, & OvGPA_i^* < 4 \\ 4, & \text{if } OvGPA_i^* \geq 4 \end{cases} \end{aligned} \quad (1)$$

where the regressors are the GRE score for analytical writing, $AGRE_i$; GRE score for verbal reasoning, $VGRE_i$; GRE score for quantitative reasoning, $QGRE_i$; prior degree program GPA, $PriorGPA_i$; the indicator variable DOI_i indicates a domestic student; indexed on student i , β_0 is the intercept, β_1 – β_5 are parameter coefficients, and the error term e_{1i} is independent and normally distributed. Even though GPA cannot exceed 4.0, most research has not used Tobit analysis when evaluating how general admittance information predicts success; therefore, the Tobit analysis used here represents a minor advancement beyond previous research.

4.3. Semesters to Graduation

One question of interest is: What background information helps predict the number of semesters to graduation? In this case, the dependent variable is treated as continuous and indicates the number of semesters for MS or PhD students to complete their degree. OSU's MS degree programs typically require

² Paper files were kept only on students who enrolled, and that is how the information was obtained. We have information on students who did not enroll starting in 2015. We estimated selectivity models using this data in spite of the time mismatch. The data show the expected in that those not offered had slightly lower grades and slightly lower GRE scores, while those offered and who did not attend had slightly higher scores. The null hypothesis of no selectivity bias was not rejected for any of the models.

three semesters of coursework in the fall and spring of the first year and fall of their second year and research hours during the summer semester and spring of their second year. The PhD program is intended to be a 3-year program, with courses taken the first 2 years and the third year devoted to research. This is faster than many other PhD programs, and the key to making it work is that students typically begin dissertation research as early as their first semester. The semesters to graduation models for students (Equation 2) were estimated in Stata using the *regress* command (StataCorp 2021).

The equation with the dependent variable semesters to graduation (*Semesters_i*) is

$$\begin{aligned} \text{Semesters}_i = & \beta_6 + \beta_7 \text{AGRE}_i + \beta_8 \text{VGRE}_i + \beta_9 \text{QGRE}_i \\ & + \beta_{10} \text{PriorGPA}_i + \beta_{11} \text{DOI}_i + e_{2i}, \end{aligned} \quad (2)$$

where *AGRE_i*, *VGRE_i*, *QGRE_i*, *PriorGPA_i*, and *DOI_i* are as defined in equation (1) are indexed on student *i*, β_6 is the intercept, $\beta_7 - \beta_{11}$ are coefficients. Separate regressions are estimated for MS and PhD students.

4.4. Grades in Core Courses

Grades at OSU are assigned using a 4.0 scale with 0 being an “F” and 4 being an “A.”³ Since there is an order to the grading scale from greatest to least, the dependent variable is an ordinal categorical variable. So, the most appropriate model for the grades in the core classes is an ordered logit regression (Long and Freese 2014; Greene 2018; Huseynov et al. 2025).

For Mathematical Economics, Linear Regression, Econometrics, Advanced Econometrics and Microeconomic Theory II, a grade classification of 2 means the student earned a C; a classification of 3 is the student earned a B; and a classification of 4 means the student earned an A. For Advanced Mathematical Programming, no student earned below a B, and so only the last two classifications were included. All core class grade models were estimated in Stata using the *ologit* command (StataCorp 2021). Data for students who withdrew were not included, since they generally withdrew for nonacademic reasons.

4.4.1. MS Program Core Classes

The equation used to estimate the ordered categorical dependent variable MS Class (*MSClass_i*) is

3 The exception was spring 2020 when Pass/Fail grades were available for undergraduate courses during forced online instruction due to COVID.

$$\begin{aligned}
MSClass_i^* &= \beta_{12}AGRE_i + \beta_{13}VGRE_i + \beta_{14}QGRE_i \\
&\quad + \beta_{15}PriorGPA_i + \beta_{16}DOI_i + e_{3i}, \\
MSClass_i &= 2 \text{ if } MSClass_i^* < \mu_1, \\
MSClass_i &= 3 \text{ if } \mu_1 \leq MSClass_i^* < \mu_2, \\
MSClass_i &= 4 \text{ if } MSClass_i^* \geq \mu_2,
\end{aligned} \tag{3}$$

where $AGRE_i$, $VGRE_i$, $QGRE_i$, $PriorGPA_i$, and DOI_i are defined as in equation (1) and indexed on student i , $\beta_{12} - \beta_{16}$ are parameter coefficients, and the error term is e_{3i} . The latent variable $MSClass_i^*$ provides thresholds (μ_1 and μ_2) for a student's possible grade moving between a C to a B or from a B to an A. $MSClass_i$ is the true grade and is 4 for an A, 3 for a B, and 2 for a C.

4.4.2. Doctoral Program Core Classes

The latent-variable equation for the ordered categorical dependent variable PhD Class ($PhDClass_i$) is

$$\begin{aligned}
PhDClass_i^* &= \beta_{17}AGRE_i + \beta_{18}VGRE_i + \beta_{19}QGRE_i \\
&\quad + \beta_{20}PriorGPA_i + \beta_{21}DOI_i + e_{4i}, \\
PhDClass_i &= 2 \text{ if } PhDClass_i^* < \mu_1, \\
PhDClass_i &= 3 \text{ if } \mu_1 \leq PhDClass_i^* < \mu_2, \\
PhDClass_i &= 4 \text{ if } PhDClass_i^* \geq \mu_2,
\end{aligned} \tag{4}$$

where $AGRE_i$, $VGRE_i$, $QGRE_i$, $PriorGPA_i$, and DOI_i are as defined in equation (1) and are indexed on student i , $\beta_{17} - \beta_{21}$ are parameter coefficients, and the error term e_{4i} . The latent variable $PhDClass_i^*$ is similar to $MSClass_i^*$.

5. Results

5.1. Empirical Regression Results

The results are organized by measures of student success: overall program GPA, time to graduation and degree completion, and grades in core courses. Results are reported separately for MS and PhD students.

5.1.1. Overall GPA Variables

Coefficient estimates for overall GPA ($OVGPA$) are shown in [Table 5](#). Of the five explanatory variables in the MS model, three are significant at $p \leq 0.05$ (or smaller) and two are significant at $p \leq 0.01$. The coefficient of prior GPA ($PriorGPA$) has a positive impact of 0.51 of a grade point. Results of prior GPA are similar to Ethridge and Hudson's (1996) findings for an agricultural economics program and Graham's (1991) findings in undergraduate GPA as

Table 5. Tobit estimates for overall grade point average (GPA) model

Variable	Estimate	Standard Error	t-Value	Pr > t
MS program ($N = 90$)				
Intercept	1.29*	0.37	3.41	0.001
Prior GPA	0.51*	0.10	5.19	<0.001
Domestic student	0.28*	0.12	2.23	0.03
GRE Analytical sub-score	0.14*	0.05	2.61	0.01
GRE Verbal sub-score	0.0003	0.0008	0.25	0.80
GRE Quantitative sub-score	-0.00006	0.0006	-0.1	0.90
PhD program ($N = 53$)				
Intercept	2.97*	0.92	3.22	<0.01
Prior GPA	0.31	0.22	1.41	0.17
Domestic student	-0.08	0.10	-0.80	0.43
GRE Analytical sub-score	-0.10	0.07	-1.46	0.15
GRE Verbal sub-score	-0.0004	0.0006	-0.01	1.00
GRE Quantitative sub-score	-0.0002	0.0004	-0.54	0.59

Notes: * $P \leq 0.05$.

a predictor of first-year average GPA. In contrast, Abedi (1991) found undergraduate GPA to not be a significant predictor regarding MS student GPA.

The domestic student (DOI) coefficient is positive and statistically significant, indicating domestic students averaged a final program GPA 0.28 above international students with similar scores. During this time period, most international MS students were not on departmental funding. Many were funded through the Fulbright Foreign Student Program, United States Agency for International Development, or their home country. These programs may have funded students from countries with less rigorous undergraduate training or selected students for other reasons than academic strengths. For PhD students, the domestic or international classification of the student was not significant. PhD students were typically funded by the department and had an MS degree from a US university or from a well-recognized university in another country such as South Korea.

The coefficient of GRE analytical sub-score (AGRE) is positive and statistically significant, which means a 1-point increase in GRE analytical sub-score (for 2025, a 3.0 was at the 17th percentile and a 4.0 was at the 63rd percentile) increases an MS student's predicted final program GPA by 0.14 grade points, which mirrors Sharon (1972). Moneta-Koehler et al. (2017) found that GRE was a moderate predictor of overall GPA lending further support for GRE scores in measuring success. The joint tests show that GRE sub-scores were statistically significant for overall GPA in the MS student

Table 6. Estimates for semesters to graduation model

Variable	Estimate	Standard Error	t Value	Pr > t
MS program ($N = 71$)				
Intercept	15.27*	2.37	6.44	<0.001
Domestic student	-0.91	0.96	-0.95	0.35
Prior program GPA	-1.73*	0.63	-2.75	0.01
GRE Analytical sub-score	-0.68	0.35	-1.95	0.06
GRE Verbal sub-score	-0.02*	0.01	-2.53	0.01
GRE Quantitative sub-score	0.01*	0.004	2.71	0.01
PhD program ($N = 39$)				
Intercept	0.83	7.81	0.11	0.92
Domestic student	1.37	0.90	1.53	0.14
Prior program GPA	2.75	3.72	0.74	0.46
GRE Analytical sub-score	-0.35	0.56	-0.63	0.54
GRE Verbal sub-score	0.003	0.005	0.74	0.46
GRE Quantitative sub-score	-0.003	0.003	-0.87	0.39

Notes: * $P \leq 0.05$.

model but not in the doctoral student model. Analytical GRE scores have a smaller standard deviation than prior GPA, so we can say that prior GPA has a standardized regression coefficient multiple times larger than GRE scores.⁴

5.1.2. Semesters to Graduation

Coefficient estimates for semesters to graduation for MS and PhD degrees are shown in [Table 6](#). Of the five variables in the MS program model, three are significant at $p \leq 0.05$. The coefficients of GRE verbal sub-score (*VGRE*) and prior GPA (*PriorGPA*) are negative and statistically significant, so higher GRE sub-scores and prior GPA are associated with shorter times to graduation. The quantitative GRE scores, however, are associated with longer times to graduation. As with the overall GPA model, standardized regression coefficients would indicate that prior GPA is multiple times as impactful as the GRE scores. None of the variables in the doctoral program model are significant at $p \leq 0.10$. These results indicate that GRE scores are not strong predictors of doctoral semesters to graduation, similar to Moneta-Koehler et al. (2017). However, there is a caveat. Some top PhD students targeting an academic career are encouraged to extend their program to 4 years to complete more coursework and publish research articles. This confounds the results since the data do not indicate if students chose an extended program for career reasons.

A probit model was estimated with finishing the degree or not as the dependent variable and results are shown in [Table 7](#). The model results in [Table 7](#) and joint tests for the significance of all three GRE sub-scores indicate that the background variables have limited ability to predict program completion. The joint test and probit results showed insignificance for GRE sub-scores.

⁴ Standardized regression coefficients are unitless alternatives to elasticities. A standardized regression coefficient is the regression coefficient times the ratio of the regressors standard deviation and dependent variable's standard deviation.

Table 7. Probit estimates for finishing the program

Variable	Estimate	Standard Error	z Value	Pr > z
MS program ($N = 82$)				
Intercept	-1.88	3.10	-0.61	0.54
Domestic student ^a				
Prior program GPA	1.10	0.73	1.51	0.13
GRE Analytical sub-score	0.22	0.52	0.42	0.68
GRE Verbal sub-score	-0.01	0.01	-1.43	0.15
GRE Quantitative sub-score	0.004	0.004	1.00	0.32
PhD program ($N = 39$)				
Intercept	-0.11	4.62	-0.02	0.98
Domestic student	0.35	0.51	0.69	0.49
Prior program GPA	0.33	1.10	0.30	0.76
GRE Analytical sub-score	-0.10	0.38	-0.26	0.79
GRE Verbal sub-score	0.005	0.004	1.38	0.17
GRE Quantitative sub-score	-0.003	0.002	-1.66	0.10

Notes: ^aNot included due to too few observations.

The findings contrast with Feeley et al. (2005), who found international students were much more likely to graduate from a communications master's program. One possible explanation is that due to funding, most domestic and international students finished their degrees.

5.1.3. GPA in MS Program Core Classes

Coefficient estimates for Mathematical Economics, Linear Regression, and Econometrics in their *MSClass* model are shown in Table 8. Of the five variables in the Mathematical Economics model, only three variables are significant, prior GPA at $p \leq 0.01$, GRE analytical sub-score, and a domestic student classification at $p \leq 0.05$. The grading scale includes A, B, or C letter grades. As with previous MS models, a higher prior undergraduate GPA had a positive marginal effect of 0.63, while a higher analytical score had a much lower marginal effect of 0.13.

Of the five variables in the Linear Regression grades model, only prior GPA is significant at $p \leq 0.05$. The results indicate a higher prior undergraduate GPA is associated with a higher grade. While the verbal sub-score and domestic classification have unexpected negative coefficients, both are insignificant.

Of the five variables in the MS Econometrics grade model, two are significant at $p \leq 0.05$: domestic student classification ($p = 0.01$) and GRE-analytical sub-score ($p = 0.01$). Both being a domestic student and having a higher analytical score were related to earning higher econometrics grades. The GRE analytical sub-score was statistically significant in two of the models. Interestingly, the analytical sub-score was largely ignored by the admissions committee during this time, while the quantitative score was weighted heavily. The quantitative score may be less predictive because many admitted students had good quantitative scores.

Table 8. Ordered logit marginal effects for MS core courses model

Variable	Estimate	Standard Error	z Value	Pr > z
Linear regression ($N = 85$)				
Domestic student	-0.005	0.16	-0.03	0.98
Prior program GPA	0.29*	0.13	2.34	0.02
GRE Analytical Sub-score	0.09	0.07	1.25	0.22
GRE Verbal Sub-score	-0.0006	0.002	-0.33	0.74
GRE Quantitative Sub-score	0.001	0.001	0.86	0.39
Mathematical Economics ($N = 86$)				
Domestic student	0.37*	0.16	2.35	0.02
Prior program GPA	0.63*	0.09	6.61	<0.01
GRE Analytical Sub-score	0.13*	0.06	2.30	0.02
GRE Verbal Sub-score	0.00004	0.001	0.04	0.97
GRE Quantitative Sub-score	0.00006	0.0006	0.10	0.92
Econometrics ($N = 74$)				
Domestic student	0.43*	0.16	2.72	0.01
Prior program GPA	0.17	0.15	1.16	0.25
GRE Analytical Sub-score	0.24*	0.07	3.35	0.01
GRE Verbal Sub-score	-0.0008	0.001	-0.68	0.49
GRE Quantitative Sub-score	0.0008	0.0007	1.08	0.28

Notes: The reported marginal effects are for the probability of receiving an A. * $P \leq 0.05$.

5.1.4. Doctoral Program Core Classes

Coefficient estimates for Microeconomic Theory II, Advanced Econometrics, and Advanced Mathematical Programming in the *PhDClass* models are shown in [Table 9](#). Of the coefficients in [Table 9](#), only prior GPA in Advanced Econometrics is significant at $p \leq 0.05$ and has the expected sign. A few other variables are significant at $p \leq 0.10$ but have unexpected signs. So, little predictability is shown, as in the other PhD models. What little significance is here indicates that prior GPA is relatively more important than GRE scores as in the MS models. The meta-analysis of Feldon et al. (2024) found that while GRE scores were positive and significant for the pooled model, most studies did not find GRE scores to be statistically significant. The results here are also consistent with Feldon et al. in finding that prior GPA was relatively more important than GRE scores. Feldon et al. found GRE scores added only 2.56 percent of predictability for year one GPA and about 4 percent predictability for overall GPA with insignificant effects in 62.3 percent of the GRE studies observed (Feldon et al. 2024).

6. Conclusions and Discussion

The question addressed here is how helpful is graduate application information in predicting student success? To answer this question, this research estimated the impact of various applicant-supplied information in models predicting student performance in OSU's Department of Agricultural Economics graduate program.

Table 9. Ordered logit marginal effects for PhD core courses model

Variable	Estimate	Standard Error	z Value	Pr > z
Microeconomic Theory II (n=51)				
Domestic student	0.02	0.14	0.11	0.91
Prior program GPA	0.22	0.29	0.75	0.45
GRE Analytical Sub-score	-0.17**	0.08	-2.03	0.04
GRE Verbal Sub-score	-0.0004	0.0008	-0.52	0.60
GRE Quantitative Sub-score	0.0004	0.0005	0.79	0.42
Advanced Econometrics (n=44)				
Domestic student	-0.23*	0.12	-1.82	0.07
Prior program GPA	0.65**	0.26	2.46	0.01
Analytical Sub-score	0.15	0.09	1.62	0.11
GRE Verbal Sub-score	-0.001*	0.0008	-1.76	0.08
GRE Quantitative Sub-score	0.0008	0.0005	1.52	0.13
Advanced Mathematical Programming (n=48)				
Domestic student	-0.04	0.14	-0.32	0.75
Prior program GPA	0.26	0.26	1.00	0.32
GRE Analytical Sub-score	-0.10	0.10	-1.04	0.30
GRE Verbal Sub-score	0.006	0.01	0.70	0.48
GRE Quantitative Sub-score	-0.001	0.003	-0.46	0.75

Notes: The reported marginal effects are for the probability of receiving an A. * $p \leq 0.10$; ** $p \leq 0.05$.

Success measures used were program GPA, semesters to graduation, and GPA in core courses. Data used to predict these success measures were GRE sub-scores for analytical, verbal, and quantitative scores, nationality, and prior program GPA. Historical data from 358 MS and PhD students were used. Regressions were estimated separately for MS and PhD students.

Prior program GPA was the most consistent indicator of students' success across all models. Performance in the MS program was more predictable than performance in the PhD program, which could be partly due to the smaller number of observations on PhD students. GRE scores, especially the analytical GRE score, showed some ability to predict student performance. The general insignificance of GRE scores supports the findings in a recent meta-analysis by Feldon et al. (2024). While the results suggest that dropping GRE scores may not be a large loss of information, we caution against that interpretation as selectivity bias likely causes the usefulness of GRE scores to be underestimated.

Our results apply to enrolled students because we do not have complete data on students who were denied admission. Also, the data are only for one university. Even so, given the consistency of the results with those of other research, the implication for graduate admission committees is to weight grades more heavily than GRE scores. It also suggests considering other information such as research productivity and time spent employed as an undergraduate.

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About the Authors

A. Leann Westbrook is a PhD candidate, Eric A. DeVuyst is a professor and Rainbolt Chair of Agricultural Finance, and B. Wade Brorsen is a regents professor and A. J. and Susan Jacques Chair in the Department of Agricultural Economics at Oklahoma State University.

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Conflicts of Interest

The authors declare no financial conflict of interest. Both Brorsen and DeVuyst were members of the graduate admissions committee during the time period of the study.

AI Disclosure

Claude Opus 4.8 and ChatGPT Plus were used to proofread the final draft. The authors reviewed and entered all changes and take responsibility for the final manuscript.

Human Subjects Disclosure

The research was approved by the Institutional Review Board of Oklahoma State University (#21-160-STW).

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REFERENCES

- Abedi, J. 1991. "Predicting Graduate Academic Success from Undergraduate Academic Performance: A Canonical Correlation Study." *Educational and Psychological Measurement* 51: 151–60. <https://doi.org/10.1177/0013164491511014>.
- Carretta, T. R., and M. J. Ree. 2023. "Corrections for Range Restriction: Lessons from 20 Research Scenarios." *Military Psychology* 34 (5): 551–69. <https://doi.org/10.1080/08995605.2021.2022067>.
- Duckworth, A., and J. J. Gross. 2014. "Self-Control and Grit: Related but Separable Determinants of Success." *Current Directions in Psychological Science* 23: 319–25. <https://doi.org/10.1177/0963721414541462>.
- Duckworth, A. L., P. D. Quinn, and E. Tsukayama. 2012. "What No Child Left Behind Leaves Behind: The Roles of IQ and Self-Control in Predicting Standardized Achievement Test Scores and Report Card Grades." *Journal of Educational Psychology* 104 (2): 439–51. <https://doi.org/10.1037/a0026280>.
- Educational Testing Service. 2020. "2020-2021 Interpreting Your GRE Scores." https://web.archive.org/web/20211102093349/https://www.ets.org/s/gre/pdf/gre_interpreting_scores.pdf.
- Ethridge, D., and D. Hudson. 1996. "Can We Predict Student Success in Agricultural Economics Graduate Programs?" *Journal of Agribusiness* 14 (2): 157–71. <https://doi.org/10.22004/ag.econ.90394>.
- Feeley, T. H., V. M. Williams, and T. J. Wise. 2005. "Testing the Predictive Validity of the GRE Exam on Communication Graduate Student Success: A Case Study at University at Buffalo." *Communication Quarterly* 53 (2): 229–45. <https://doi.org/10.1080/01463370500090209>.
- Feldon, D. F., K. Litson, B. Cahoon, Z. Feng, A. Walker, and C. Tofel-Grehl. 2024. "The Predictive Validity of the GRE Across Graduate Outcomes: A Meta-Analysis of Trends Over Time." *The Journal of Higher Education* 95 (1): 120–48. <https://doi.org/10.1080/00221546.2023.2187177>.
- Graham, L. D. 1991. "Predicting Academic Success of Students in a Master of Business Administration Program." *Educational and Psychological Measurement* 51: 721–27. <https://doi.org/10.1177/0013164491513023>.
- Greene, W. H. 2018. *Econometric Analysis*. 8th ed. Pearson.
- Heckman, J. 1990. "Varieties of Selection Bias." *American Economic Review* 80 (2): 313–18. <https://www.jstor.org/stable/2006591>.
- Hirschberg, N., and S. Itkin. 1978. "Graduate Student Success in Psychology." *American Psychologist* 33 (12): 1083–93. <https://doi.org/10.1037/0003-066X.33.12.1083>.
- House, J. D., and J. J. Johnson. 1993. "Graduate Record Examination Scores and Academic Background Variables as Predictors of Graduate Degree Completion." *Educational and Psychological Measurement* 53: 551–57. <https://doi.org/10.1177/0013164493053002025>.
- Huseynov, S., C. N. Boyer, C. C. Martinez, A. Griffith, and K. L. DeLong. 2025. "The Role of Recency Bias and Price Salience in Insurance Take-Up Decisions." *Journal of Agricultural and Resource Economics* 50 (1): 21–38. <https://doi.org/10.22004/ag.econ.344679>.
- Long, J. S., and J. Freese. 2014. *Regression Models for Categorical Dependent Variables Using Stata*. 3rd ed. Stata Press.
- Manhattan Review. 2021. "GRE Info – GRE History." <https://www.manhattanreview.com/gre-history/>.

- Matthews, T. A., and D. J. Martin. 1992. "Reciprocal Suppression and Integration Effects of Age with Undergraduate Grades and GRE on Graduate Performance in a College of Education." *Educational and Psychological Measurement* 52: 453–57. <https://doi.org/10.1177/0013164492052002021>.
- McDonald, J. F., and R. A. Moffitt. 1980. "The Uses of Tobit Analysis." *Review of Economics and Statistics* 62: 318–21. <https://doi.org/10.2307/1924766>.
- McKee, A. J., S. L. Mallory, and J. Campbell. 2001. "The Graduate Record Examination and Undergraduate Grade Point Average: Predicting Graduate Grade Point Averages in Criminal Justice Graduate Program." *Journal of Criminal Justice Education* 12 (2): 311–17. <https://doi.org/10.1080/10511250100086141>.
- Moneta-Koehler, L., A. M. Brown, K. A. Petrie, B. J. Evans, and R. Chalkley. 2017. "The Limitations of the GRE in Predicting Success in Biomedical Graduate School." *PLoS One* 12 (1): e0166742. <https://doi.org/10.1371/journal.pone.0166742>.
- New Mexico State University. 2023. "Graduate Programs." <https://aeab.nmsu.edu/graduate/graduate-program.html>.
- Oklahoma State University, Department of Agricultural Economics. 2019. *Graduate Handbook*.
- Rimfeld, K., Y. Kovas, P. S. Dale, and R. Plomin. 2016. "True Grit and Genetics: Predicting Academic Achievement from Personality." *Journal of Personality and Social Psychology* 111 (5): 780–89. <https://doi.org/10.1037/pspp0000089>.
- Sackett, P. R., and H. Yang. 2000. "Correction for Range Restriction: An Expanded Typology." *Journal of Applied Psychology* 85 (1): 112–18. <https://doi.org/10.1037/0021-9010.85.1.112>.
- Sharon, A. T. 1972. "English Proficiency, Verbal Aptitude, and Foreign Student Success in American Graduate Schools." *Educational and Psychological Measurement* 32: 425–31. <https://doi.org/10.1177/001316447203200219>.
- StataCorp. 2021. *Stata Statistical Software, Release 17*. StataCorp LLC.
- University of Arizona. 2023. "Graduate Program: Agricultural and Resource Economics (MS) – Applied Economics and Policy Analysis." <https://web.archive.org/web/20230325134330/https://grad.arizona.edu/catalog/programinfo/ARECMSAEP>.
- Wilson, R. L., and B. C. Hardgrave. 1995. "Predicting Graduate Student Success in an MBA Program: Regression Versus Classification." *Educational and Psychological Measurement* 55 (2): 186–95. <https://doi.org/10.1177/0013164495055002003>.
- Zilberman, D., J. Kozler, and W. Yan. 2025. "How to Make Agricultural and Resource Economics More Relevant, Interesting, and Efficient." *Journal of Agricultural and Resource Economics* 50 (4): 769–82. <https://doi.org/10.22004/ag.econ.369142>.