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Research Article

An Evaluation of Undergraduate Student Diversity Experiences in the College of Agriculture at Kansas State University

Lonnie Hobbs[a], Jr., Zelia Z. Wiley[a], Raymond Thomas[a], Summer Santillana[a], and Andrew Barkley[a]
[a]*Kansas State University*

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Abstract
As diverse student populations increase in colleges of agriculture at Land-Grant universities, diversity experiences are critical to the academic and personal development of undergraduate students. At Kansas State University, where enrollment of nonwhite undergraduate students has increased from 8 percent (2008) to 12 percent (2022), proper understanding of the factors that affect experiences with diverse groups is vital to foster positive diversity experiences among students. This study applies an ordinary least square (OLS) regression estimation approach to identify and quantify the determinants of positive or negative diversity experiences for students enrolled in the College of Agriculture (COA) at Kansas State University. Data were collected in a survey during Fall 2020, with 359 observations included in the analysis. The period is unique due to the Covid-19 pandemic, causing the data to be particularly informative. The level of diversity experiences is found to be statistically associated with participation in diversity class activities and workshops, ethnic background, small-town background, degree being sought, and living situation. However, student diversity experience levels were relatively low. Overall, the results show that student diversity experiences could be increased through the implementation and promotion of diversity programming based on the determinants of diversity experiences identified in this study.

1 Introduction

Creating a diverse campus environment through positive diversity experiences is crucial to the academic and personal development of undergraduate students. Student experiences with diversity is defined as a measure of the degree to which students have interacted with individuals different from themselves in race, ethnicity, philosophy of life, political view, religious beliefs, or country of origin. It has been well documented that student involvement with diversity experiences positively impacts the overall college student experience and career preparation (Hurtado 2001; Jayakumar 2008; Carter, Hobbs, and Wiley 2019). Learning how to work and interact with individuals from various ethnic, cultural, and professional backgrounds can lead to more positive diversity interactions, creating a more inclusive campus environment for both undergraduate and graduate students.

Diversity experiences also provide students an opportunity to learn from the perspective of others (Pedlar and Tirone 2005) while increasing comfortability and confidence in their own identity (Phinney 1990; Cross 1991; Helms 1993; Pedlar and Tirone 2005) and providing a more inclusive environment in which students feel they belong (Hurtado 1992; Smith and Schonfeld 2000; Smith 2020). Moreover, students need experiences with diversity so they can better understand the value of tolerance and teamwork in their academic and professional careers (Smith and Schonfeld 2000; Brief 2008; Smith 2020), as well as in their own personal lives (Smith and Schonfeld 2000; Whitt et al. 2001; Smith 2020). Increased diversity experiences through proper implementation of diversity programs at universities can foster student inclusivity and belongingness (Gurin 1999; Smith and Schonfeld 2000; Brief 2008;

Smith 2020), likely leading to increased enrollment and retention of diverse students (Barkley et al. 2021).

Students attending primarily white institutions, such as Kansas State University may not be presented with situations in which they are exposed to diversity as regularly as the environments students could find themselves in after graduating (Brief 2008; Smith 2020). Therefore, primarily white institutions have an increased need to provide opportunities for experiences with diverse populations through the implementation of programs and courses focused on the topics of diversity and inclusion in an academic and professional setting (Smith and Schonfeld 2000; Alston, Roberts, and English 2019; Smith 2020). Furthermore, it is essential that students' diversity experiences are measured and analyzed to ensure that steps are taken to provide programming that promotes an equitable and inclusive campus for all students.

Previous studies highlight the benefits of diversity experiences among college students, yet literature focused on the determinants of those diversity experiences is still limited. Hu and Kuh (2003) found that the promotion of diverse interaction in learning and living environments positively impacts student diversity experience levels. Also, it has been reported by Chang et al. (2006) that greater diversity exposure and interaction prior to attending college increases the diversity experiences while at college, whereas Bowman (2011) found that diversity experiences are influenced by civic attitudes, behavioral intentions, and interpersonal interactions. Likewise, Barkley et al. (2021) identified that factors such as class discussion surrounding topics of diversity, diversity workshops, ethnicity, parent education, and student's field of study affects the level of openness to diversity among students. Moreover, these studies provide empirical evidence that personal characteristics, academic characteristics, participation in diversity workshops, and class discussions about diversity are key factors that affect student experiences with diversity.

Although these factors can impact students' diversity experiences while on campus, previous research also identifies students' feelings about these factors as an important predictor of the type of diversity experiences the student receives (Dickson, Jepsen, and Barbee 2008). More specifically, a student's feelings about the environment created by diversity programs and workshops determine the student's attitude and acceptance of diversity experiences. Thus, to foster an inclusive environment, the factors which lead to positive diversity experiences must be known.

The purpose of this study is to identify and quantify the determinants of the level of feelings associated with diversity experiences among enrolled students in the College of Agriculture (COA) at Kansas State University during Fall 2020 semester. More specifically, we utilize survey data to measure student levels of diversity experiences through interaction and feelings during exchanges with diverse students in the COA during the COVID-19 pandemic. This study utilizes a similar approach to Hu and Kuh (2003), Chang et al. (2006), and Barkley et al. (2021) to identify the feelings associated with students' experiences with diversity. Denson and Chang (2009) identified three forms of racial diversity in higher education that are evident in person and can be observed virtually: (1) structural diversity (racial composition of enrolled students), (2) curricular and co-curricular diversity (diversity programming targeted at enhanced knowledge of diversity), and (3) interaction diversity (informal relationships and interactions between enrolled students). This study provides a measure of curricular and co-curricular diversity and interaction diversity, exemplified by the Diversity Programs Office within the COA at Kansas State University.

The Diversity Programs Office seeks to implement and maintain curricular and co-curricular diversity experience programs, as well as promote diversity interactions within other departments in the COA. These curricular and co-curricular programs include the biennial "Growing our Mindset" forum, Project Impact Multicultural Academic Programs Success, and Project Impact KOMPASS, as well as two diversity-related classes (Carter et al. 2019). Each of which were historically attended in person but transitioned into virtual or hybrid programs for the duration of the COVID-19 pandemic. These programs are important because of the critical mass of multicultural populations in the COA. Smith and

Schonfeld (2000) state, "The numbers of diverse people, or more specifically the presence of a critical mass of diverse people, create greater opportunities for social support, role models, and mentors. Having diversity in the population creates greater opportunity for individuals to be seen as individuals, thus breaking down stereotypes" (p. 18).

The major implication of the statistical results implies that there exists an opportunity to increase student diversity experience levels through the implementation and promotion of diversity programs such as workshops and academic courses that enhance interaction and openness to people with different backgrounds, experiences, and beliefs. As a result, these programming efforts can be applied to the COA at Kansas State University, as well as other higher education institutions to increase student self-reported learning, personal development outcomes, and openness toward people from backgrounds different than themselves. This, in turn, has the potential to lead to increased recruitment and retention of underrepresented student populations.

It is essential that COA faculty, administrators, staff, and students understand the factors that affect diversity experiences, to help create a more inclusive campus/learning environment for all students. In what follows, we provide a literature review in the next section, followed by methodology in Section 3 and data in Section 4. The results of the study are found in Section 5, discussion in Section 6, and conclusions in Section 7.

2 Background and Previous Research

Students with greater openness to diversity and challenge are more likely to participate in diversity experiences. Openness to diversity and challenge developed through diversity experiences can have a large impact on changes in student attitudes, beliefs, and actions in the direction of greater tolerance to individual differences (Whitt et al. 2001). In addition, it has been shown that interactions with persons from different backgrounds can lead to positive impacts on self-reported learning and personal development outcomes. This shows the importance of diversity experience research to improve upon this aspect of student learning (Pedlar and Tirone 2005). Hu and Kuh (2003) used responses from over 53,000 undergraduate students enrolled in 124 American universities to examine the effects of diversity experiences. The results from this survey demonstrated that white students had a smaller number of interactions with students from a different background than with other white students.

Students who are from different backgrounds perceive diversity interactions in relation to their backgrounds and prior experiences. Providing diverse interaction opportunities aids in the development of an appreciation for personal practices, as well as those of other cultures (Pedlar and Tirone 2005). While diversity programs provide benefits, it is important to note that Dickson et al. (2008) found that ambience and feelings of students toward these programs is a significant predictor of positive cognitive attitudes toward issues of racial diversity. This finding shows the importance of creating a culturally sensitive environment within diversity experience programs, rather than creating a generic program. Therefore, when implementing programs and events that foster interactions and knowledge from across cultural groupings, the demographic groups involved must be considered and recognized (Gurin 1999; Gurin et al. 2002; Gurin and Nagda 2006).

The level of diversity experiences while on university campuses is affected by several personal and academic characteristics. For instance, Pascarella et al. (1996) found that students who lived on campus, studied the most, and were most engaged with their student peers tended to have the highest levels of openness to diversity, which in turn has been linked to higher levels of diversity interaction. Milem and Umbach (2003) studied how student plans for involvement in diversity-related activities in college varied across race, personality type, and experiences with diversity. The authors concluded that white students are the least likely to be prepared for diversity experiences and interactions in college. Students who selected social and artistic majors were more likely to plan to participate in diversity experiences, and personality has an influence on self-reported desire to engage in diversity experiences

(Milem and Umbach 2003). As noted, there are significant demographic factors that must be accounted for within school-related diversity experience programs (Gurin 1999; Gurin et al. 2002; Gurin and Nagda 2006). However, the location and format in which the diversity interaction takes place are also important (Gurin 1999; Gurin et al. 2002; Gurin and Nagda 2006).

Previous studies have shown the importance of diversity programming such as diversity courses, workshops, and class discussions (Gurin 1999; Gurin et al. 2002; Gurin and Nagda 2006). Demographic variables such as gender, year in college, and race/ethnicity are often included in survey research to identify and quantify differences between groups (Whitt et al. 1999; Whitt et al. 2001; Milem and Umbach 2003; Shim and Perez 2018; Alston et al. 2019). Previous research also demonstrated that a student's community of origin reflects exposure to racial diversity (Milem and Umbach 2003). Likewise, a student's peer group while enrolled in college often reflects experiences with and interaction with persons who are different from themselves (Gurin 1999; Whitt et al. 2001; Gurin et al. 2002; Milem and Umbach 2003; Gurin and Nagda 2006). In the next section, we discuss variables included in the survey to measure a student's community prior to entering college and peer group while enrolled in college.

3 Methodology

This study examines data collected via survey to assess the determinants for positive and negative diversity experiences of undergraduate students enrolled in the COA at Kansas State University. Econometric analysis using ordinary least square (OLS) regression provides a quantitative estimate of the impact of personal characteristics and college experiences on student diversity experiences. To identify the determinants of the experiences with diversity (DIVEXP), student demographic information, personal and academic characteristics, participation in diversity workshops, and class discussions about diversity were included as explanatory variables, as shown in equations (1) and (2), where i = positive or negative diversity experience, as explained below.

$$DIVEXP_i = f(\text{Diversity Workshops and Class Discussion, Personal Characteristics, Demographic Variables, Academic Characteristics}). \quad (1)$$

To estimate the effects of the above characteristics on student responses to the diversity experience questions, the function in equation (1) is further specified as an OLS regression as shown in Equation (2). Taking means and standard deviations of Likert scale variables is debated by statisticians and applied social scientists (Carifio and Perla 2007). Some researchers maintain that because Likert scales are ordered categories, the intervals between the scale values are not equal (i.e., the quantitative difference between "neutral" and "agree" may differ from the difference between "agree" and "strongly agree"; Jamieson 2004). In this view, numerical operations such as means and parametric tests are not valid representations of the data.

Others argue that parametric tests such as linear (OLS) regression using Likert scale items are valid (Glass, Peckham, and Sanders 1972; Lubke and Muthen 2004). For this study, if the underlying process of the five-point scale is assumed to be continuous, then we can also assume that the intervals between points are approximately equal. Glass, Peckham, and Sanders (1972) and Carifio and Perla (2007) showed that in most cases, the F-test is extremely robust and that parametric statistical tests can be used to analyze Likert scale data. Here, means of several similar Likert scale survey questions are used to synthesize and summarize the data into two broad categories. This is done to reduce the dimensionality of the survey results and statistical analyses of the results. Caution should be used when interpreting the results, recalling that the data come from ordinal data.

$DIVEXP_i$ represents eight survey questions, of which the first three are positive diversity experiences and the last five are negative diversity experiences. A linear regression equation is assumed where $DIVEXP_i$ is the average of the responses for the positive or negative diversity experience questions where i = 1 (if positive) and i = 2 (if negative). The mean of questions 1–3 was used to

represent the positive DIVEXP dependent variable, and the mean of questions 4–8 represented the negative DIVEXP dependent variable.[1] The error term ε_i accounts for influences on the dependent variable from sources other than the independent variables. Equation (2) shows the regression estimation equation:

$$DIVEXP_i = \beta_0 + \beta_1 DIVCRSD_i + \beta_2 DIVWORKD_i + \beta_3 DIVCLASS_i + \beta_4 COLYEAR_i + \beta_5 GENDER + \beta_6 RACE + \beta_7 COMMUNE + \beta_8 HIGHED + \beta_9 LIVING + \beta_{10} NOJOB + \beta_{11} WORKHRS + \beta_{12} STUDYHRS + \varepsilon_i. \quad (2)$$

The coefficients β_n where n = 1 . . ., 12 are partial regression weights for the independent variables detailing the respective impacts on $DIVEXP_i$, and β_0 represents the regression constant. The primary diversity variables $DIVCRSD_i$ and $DIVWORKD_i$ indicate whether a student participated in any diversity courses or workshops, with 1 indicating *participation* and 0 indicating *nonparticipation*. Additional binary variables included *GENDER*, with 0 indicating *male* and 1 indicating *female*, and student interest in seeking an advanced degree (*HIGHED*), with 1 indicating *yes* and 0 indicating *no*. The variable $DIVCLASS_i$ indicates the frequency of class discussions focused on diversity the students have experienced, with response options ranging from 1 to 4, with 1 being *Never* and 4 being *Very Often*. Independent variables for the students' demographic characteristics include: *Year in College* ($COLYEAR$) referring to the students' current year in school, *Race/Ethnicity* (*RACE,* i.e., White, Black, Hispanic, etc.), *Community of Origin (COMMUNE)* indicating the type of area a student is from based on population, *Living Situation (LIVING)* referring to the students' current living arrangement and location (i.e., on- or off-campus, house or apartment, etc.), and *Time allocation (*$NOJOB$, $WORKHRS$, $STUDYHRS$*)* indicating the students current employment status and time allocated for work and studying.[2]

4 Data

This study focuses upon survey results retrieved during Fall 2020 semester. An electronic survey was sent to 2,163 undergraduate students in the COA at Kansas State University. There were 359 students who submitted complete, usable responses, yielding a 16.6% response rate from the overall population. The diversity experience (DIVEXP) questions were taken from Shim and Perez (2018) as reported in the next section and detailed in Appendix 1. Survey respondents were asked to respond to the eight statements on a Likert scale from 1 = *Never* to 4 = *Very often.* Responses ranged between the lowest value (=1) and the highest value (=4) for each question. Questions 1–3 are used to represent positive peer interaction of students, while questions 5–8 are used to represent negative peer experiences.

The online survey was administered via email during the COVID-19 pandemic. Due to the large number of positive COVID-19 cases and student quarantines/isolation, all classes at Kansas State University were offered online per the university's remote status. Throughout Fall 2020 semester, students were sent daily emails regarding operation instructions and wellness checks during the pandemic. As a result, there was likely some degree of "survey fatigue" among students. Although the survey for this research survey was sent several times and reminder messages were sent, many students likely had a sense of information overload, resulting in fewer responses than expected. However, the

[1] Separate regressions were estimated using each of the eight diversity experience questions (reported in Table 1) as the dependent variables, using both multinomial logit and OLS techniques. Given the unwieldy regression results, we combined diversity experience questions into "positive" and "negative" groups to reduce the dimensionality of the results and make the research results more meaningful. Results were qualitatively similar to those presented in Table 3 for the average variables of DIVEXP for positive and negative student experiences.

[2] For each group of categorical variables, the variable with the highest frequency of responses is omitted from the regressions as the default category. These omitted default variables are: "Never" for diversity in class discussions and assignments, First Year Student, White, Farm/Ranch, Both Parents College, 12–14 Credit Hours, House/Drive Distance, Other Students, and Major in Animal Sciences (Table 2).

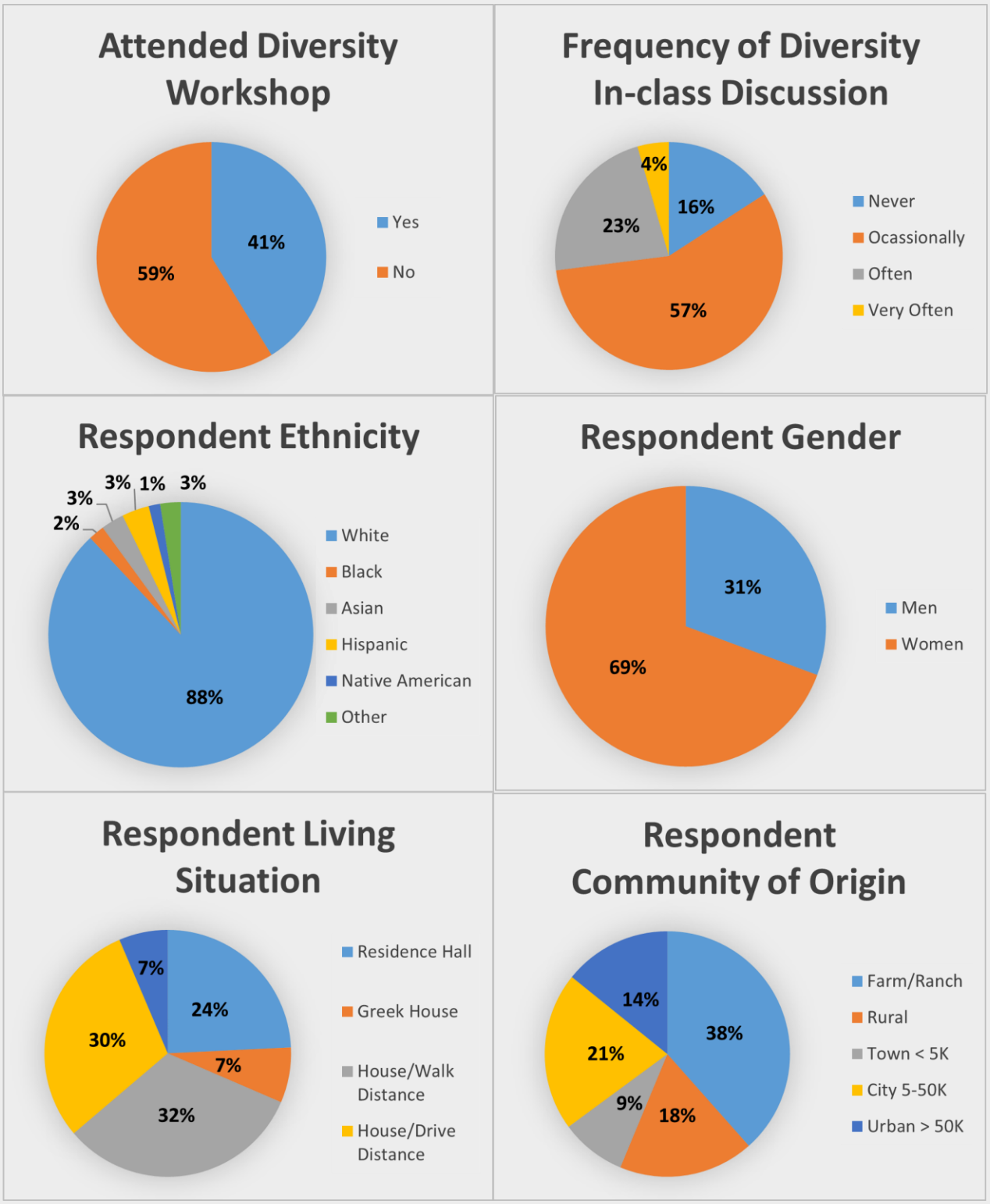

Figure 1. Data Characteristics

results are interesting and important and should be interpreted as such.

Data characteristics are displayed in Figure 1. Of the 359 COA student respondents, more than half of the sample were female students (69 percent). Regarding ethnicity, 88 percent of student respondents were Caucasian, 2 percent African American, 3 percent Hispanic, 3 percent Asian, 1 percent

Native American, and 3 percent identified as other. The respondents' community of origin included 38 percent from a farm or ranch, 18 percent from rural communities, 9 percent from towns of less than 5,000 residents, 21 percent from a city with a population of 5,000–50,000, and 14 percent from an urban area with a population greater than 50,000 people. Also, many respondents lived in a house either walking distance (32 percent) or driving distance from campus (30 percent), respectively. The remaining respondents reported living in a residence hall (24 percent), Greek house (7 percent), or other (6 percent). Forty one percent of respondents reported attendance to a diversity workshop. Regarding frequency of diversity in in-class discussion, more than half of the students (57 percent) reported occasional in-class discussion focused on diversity. In contrast, 23 percent reported participation in in-class discussions on diversity "often," 4 percent had diversity discussions "very often," and 16 percent reported "never" participating in in-class discussions on diversity.

5 Results

5.1 Descriptive Results

The degree to which survey participants are representative of the total college student population during Fall 2020 is shown in Table 1. Statistically significant differences between the sample and population are found for five of the seven categories. This is not unexpected, given the small number of observations in each category. African American and multiracial/other categories were not statistically significant. Although the sample appears to be somewhat representative, the differences between sample respondents and population means must be kept in mind as the results are interpreted.

Table 1. Fall 2020 Demographics for Kansas State University College of Agriculture

	Population	Survey	Difference	t-stat
		-----(percent)-----		
African American	2.0	2.0	0	0
American Indian/Native American	0.5	1.0	-0.5	9.61*
Asian	1.1	3.0	-2.0	12.34*
Hispanic/Latinx	4.7	3.0	1.7	11.04*
Multiracial/Other	3.2	3.0	0.2	1.31
White	85.9	88.0	-2.1	3.77*
Female	60.0	69.0	-9.0	3.68*

Note: The number of observations equals 359. The asterisk indicates statistical significance at the 10 percent level.

Descriptive statistics for survey responses are displayed in Table 2. Questions 1–3 represent the positive peer interaction of the students, examining how often the respondents engage in positive discussions with diverse students. Questions 4–8 measure the respondents' level of negative diversity experience. The mean values of the positive and negative Likert scale responses for the eight survey statements are used as a measure of the diversity interaction and experiences of undergraduate students while attending the COA at Kansas State University.

The mean of each positive experience question shows that, on average, respondents answer "Occasionally." The researchers consider this to indicate the respondents' level of positive interaction with diverse students is relatively low. The mean response for negative diversity experiences shows that, on average, respondents' answer "Never" for these questions. The researchers consider this to indicate that, on average, students are having positive diversity experiences while in the Kansas State University COA. Yet, it is suspected that this is due to the low level of interaction with diverse students. Summary statistics for the included variables in the 2020 survey are reported in Table 3, together with the regression results in Table 4.

Table 2. Survey Responses to Diversity Experience Questions (Fall 2020)

	Question	Never	Occasionally	Often	Very Often
		- - - - - - - - - - - - - - Count (%) -			
DIVEXP 1	I had discussions regarding intergroup relations with diverse students.	152 (42.34)	152 (42.34)	40 (11.14)	15 (4.18)
DIVEXP 2	I had meaningful and honest discussions about issues related to social justice with diverse students while attending this college.	130 (36.21)	139 (38.72)	61 (16.99)	29 (8.08)
DIVEXP 3	I shared personal feelings and problems with diverse students while attending this college.	140 (39.00)	138 (38.44)	56 (15.60)	25 (6.96)
DIVEXP 4	I had guarded, cautious interactions with diverse students.	219 (61.00)	106 (29.53)	26 (7.24)	8 (2.23)
DIVEXP 5	I felt silenced by discrimination from sharing my own experiences with diverse students.	257 (71.59)	74 (20.61)	16 (4.46)	12 (3.34)
DIVEXP 6	I had hurtful, unresolved interactions with diverse students.	324 (90.25)	22 (6.13)	10 (2.79)	3 (0.84)
DIVEXP 7	I had tense, somewhat hostile interactions with diverse students.	315 (87.74)	30 (8.36)	10 (2.79)	4 (1.11)
DIVEXP 8	I felt insulted or threatened based on my race, national origin, values, or religion with diverse student while attending this college.	288 (80.22)	52 (14.48)	11 (3.06)	8 (2.23)

Note: Number of observations equals 359. Survey responses are: 1 = "Never," 2 = "Occasionally," 3 = "Often," and 4 = "Very Often."

Table 3. Means of Variables Included in Diversity Experience Regression[1]

Variable	Mean
Diversity Experience	
Diversity Course	0.58
Diversity Workshop	0.41
Diversity in Class Discussions and Assignments	
Never	0.16
Occasionally	0.57
Often	0.23
Very Often	0.04
Year in College	
Freshman	0.24
Sophomore	0.23
Junior	0.23
Senior	0.25
Five or more years	0.05
Personal Characteristics	
Female	0.69
Age (years)	20.0
Race/Ethnicity	
White	0.88
Black/African American	0.02
Asian/Asian American	0.03
Hispanic/Latinx	0.03
Native American	0.01
Other	0.03
Community of Origin	
Farm/Ranch	0.38
Rural Area	0.18
Town <5,000 people	0.09
City 5,000-50,000 people	0.21
Urban >50,000 people	0.14
Academic Characteristics	
Seek Adv. Degree	0.60

Table 3 continued

Variable	Mean
Living Situation: Location	
Residence Hall	0.24
Greek House	0.07
House/Walk Distance	0.32
House/Drive Distance	0.30
Other	0.06
Time Allocation	
No Job	0.38
Work Hours/Week	11.21
Study Hours/Week	14.23

Note: The Number of observations equals 359.

5.2 Estimation Results

Table 4 displays the results from the OLS estimation for positive ($DIVEXP_1$) and negative ($DIVEXP_2$) diversity experience questions. Each independent variable administered as a multiple-choice option on the survey uses a base (default) option indicated by "–" in the results table.

Examining $DIVEXP_1$ results, attendance in diversity workshops (*DIVWORKD*) increased the likelihood of positive diversity experiences with an estimated coefficient equal to 0.22 ($p < 0.01$). Likewise, the variable for class discussions on diversity (*DIVCRSD*) is also significant with positive coefficients at all response levels. These results of *DIVCRSD* show the mean for positive response questions increase on the four-point Likert scale as the quantity of in-class discussion and assignments on diversity-related topics increases.

This is displayed as the coefficient for each response level increased from 0.27 ($p < 0.05$) for "Occasional" discussion to 0.49 ($p < 0.01$) and 0.95 ($p < 0.01$) for "Often" and "Very Often," respectively. These estimated coefficients are interpreted as a change in the average response rate for the mean of the three positive experience questions: for students responding, "Occasionally," for diversity class discussions, the average response to the three positive diversity questions increased by 0.27 on the four-point Likert scale.

Ethnic identity results indicate the Hispanic/Latinx variable had a positive coefficient of 0.78 ($p < 0.01$). This result is measured against the base ethnicity Caucasian. Thus, we interpret the positive coefficient relative to the Caucasian student mean response for the positive diversity experience questions. Similarly, the community of origin results indicate a positive relationship on the $DIVEXP_1$ questions for students from urban communities with greater than 50,000 people. This is displayed through the 0.20 ($p < 0.05$). Regarding student living situations, the residence hall variable is 0.22 ($p < 0.10$). House/walk distance variable is also statistically significant with a 0.21 ($p < 0.05$). Both living situation variables were referenced to the base house/drive category and indicated higher levels of positive diversity experience.

Results for $DIVEXP_2$ displayed four statistically significant variables. The gender variable (FEMALE) is statistically significant and negative. Additionally, the estimated coefficient on age equals 0.07 ($p < 0.05$), indicating higher negative diversity experiences among older students. In contrast, the coefficient for students who originated from cities with a population of between 5,000–50,000 people is -0.15 ($p < 0.10$). Last, the independent variable indicating a student's interests in pursuing an education beyond a bachelor's degree is 0.11 ($p < 0.10$).

Table 4. Diversity Experience Regression Results[1]

Variable	*DIVEXP₁* POSITIVE EXPERIENCE		*DIVEXP₂* NEGATIVE EXPERIENCE	
	Coefficient	Standard Error	Coefficient	Standard Error
Intercept	-0.02	0.723	-0.19	0.485
Diversity Experience				
Diversity Course	0.10	0.085	0.01	0.057
Diversity Workshop	0.22***	0.083	0.07	0.056
Diversity in Class Discussions and Assignments				
Never	-	-	-	-
Occasionally	0.27**	0.106	-0.06	0.071
Often	0.49***	0.126	0.04	0.084
Very Often	0.95***	0.202	0.06	0.136
Year in College				
Freshman	-	-	-	-
Sophomore	-0.08	-.132	0.07	0.889
Junior	-0.05	0.154	0.00	0.103
Senior	-0.10	-0.175	-0.08	0.118
Five or more years	-0.02	0.261		
Personal Characteristics				
Female	-0.02	0.084	-0.12**	0.056
Age (years)	0.06	0.038	0.07***	0.025
Race/Ethnicity				
White	-	-	-	-
Black/African American	0.36	0.264	0.20	0.177
Asian/Asian American	0.23	0.226	0.13	0.152
Hispanic/Latinx	0.78***	0.203	0.12	0.136
Native American	-0.09	0.305	-0.29	0.204
Other	0.35	0.235	0.09	0.158
Community of Origin				
Farm/Ranch	-	-	-	-
Rural Area	-0.08	0.103	-0.03	0.069
Town <5,000 people	-0.14	0.137	-0.12	0.092
City 5,000-50,000 people	-0.02	0.102	-0.15	0.069**
Urban >50,000 people	0.20	0.118**	-0.10	0.079

Table 4 continued.

Variable	*DIVEXP₁* POSITIVE EXPERIENCE		*DIVEXP₂* NEGATIVE EXPERIENCE	
	Coefficient	Standard Error	Coefficient	Standard Error
Academic Characteristics				
Seek Adv. Degree	0.18	0.077	0.11**	0.051
Living Situation: Location				
Residence Hall	0.22	0.127*	0.02	0.085
Greek House	0.08	0.157	-0.04	0.105
House/Walk Distance	0.21	0.096**	-0.06	0.064
House/Drive Distance	-	-	-	-
Other	0.16	0.157	-0.10	0.106
Time Allocation				
No Job	0.01	0.117	-0.00	0.078
Work Hours/Week	0.01	0.005	0.00	0.003
Study Hours/Week	0.00	0.004	0.00	0.003
Observations	395		395	
Root MSE	0.6626		0.4447	
R-Square	0.2859		0.1385	

Note: Level of significance is denoted as: *** *p < 01; ** p < 0.05; * p < 0.10.*

6 Discussion

The diversity workshop variable for the *DIVEXP₁* regression indicates that student participation in diversity workshops increases the average response for the positive diversity experience questions by 0.22. The positive in-class discussion variable also indicates a positive relationship between in-class discussions on topics relating to diversity and positive diversity experiences on campus. Higher levels of in-class discussion and assignments related to diversity topics increases positive diversity experiences on campus. These are the main results of the survey research presented here and represent an important finding for the promotion of diversity at colleges and universities: diversity educational programs, both inside and outside of formal classroom settings, can lead to greater levels of positive diversity experiences for students.

As highlighted by Carter et al. (2019), the COA Diversity Programs Office provides diversity workshops and a course on diversity in the COA at Kansas State University. Given the positive experience results, there is a need to continue with programs and courses provided through the COA Diversity Programs Office, which fosters positive diversity experiences among students. This result provides some evidence of the positive contribution that diversity programs can provide student experiences with higher education.

Examining the race/ethnicity results for *DIVEXP₁*, Hispanic/Latinx students were more likely to respond indicating they were having positive diversity experiences when compared to the base ethnic category of Caucasian. However, it is difficult to know the cause of this result. Therefore, additional research is needed to explore the relationship between ethnicity and positive diversity experience. Regarding community of origin, *DIVEXP₁* results infer students from urban communities with greater than 50,000 people reported higher positive diversity experience on average, when compared to the default of those from a farm/ranch background. This is suspected to be due to a higher representation of

and exposure to diversity in larger urban areas, as opposed to smaller rural areas, which have been found to show lower levels of diversity (Slama 2004). This result is important for colleges and universities that have significant student populations from rural backgrounds: it may take more diversity exposure, education, and training to increase the level of positive diversity experiences of rural students to the same level as students from backgrounds other than rural.

The students' living situation indicates that students who live within walking distance of the university indicated more positive diversity experiences on campus when compared to students living in a house within driving distance of campus. As highlighted in Graham, Hurtado, and Gonyea (2018), student engagement in conversation with other diverse students tends to be higher among students who live closer to campus. The findings in Table 4 corroborate the results that living within walking distance of the university can increase positive diversity experiences. This result is important to consider when colleges and universities develop housing policies. A positive contribution to diversity experiences could be the design and implementation of diversity programs for off-campus students. However, it is important to note this result may be influenced by the COVID-19 pandemic, as students were more isolated and many lived in their hometowns during quarantine.

Regarding the $DIVEXP_2$ results, the gender coefficient indicates women have a lower average response to the negative diversity experiences on campus. Therefore, showing that women may have fewer negative diversity experiences than men. The reasoning for this could be supported by Glass and Cook (2018), who found that women were more likely to champion diversity in their respective organizations. Therefore, it is possible that women experienced lower levels of negative diversity experiences because they are more likely to be open to diversity experiences. The age coefficient for the $DIVEXP_2$ regression suggests that students who were older reported higher levels of negative diversity experiences on campus. Students interested in pursuing a higher degree (*HIGHED*) also displayed higher levels of negative diversity experiences responses on average. This result provides an area for improvement with diversity education and training programs. In contrast, the community of origin coefficient indicates students from cities with 5,000–50,000 people have fewer negative diversity experiences when compared to students from farm/ranch backgrounds. Coinciding with the urban positive experiences results in $DIVEXP_1$, students from larger city areas have more positive experiences with diverse groups. This provides evidence that diversity programming is necessary for rural students to ensure positive diversity experiences on campus.

7 Conclusions

Overall, the regression results indicate the positive and negative levels of experiences with diversity were found to be statistically associated to a variety of factors. These factors include having taken a diversity course or workshop, having diversity as a topic in class discussions and assignments, gender, race/ethnicity (Hispanic/Latinx), community of origin, seeking an advanced degree, residence hall living, and residence near or on campus. The identification of student characteristics associated with positive or negative diversity experiences allows students, faculty, and administrators information useful for addressing future institutional diversity programming objectives. Overall, these results allow for a more targeted application of diversity programming efforts.

The major implication of the statistical results is that there exists an opportunity to enhance student diversity experiences through implementation and promotion of diversity programming such as workshops and academic courses that enhance interaction and openness to people with different backgrounds, experiences, and beliefs. Although a large percentage of students did not experience feelings of hurtful, intense, or guarded actions while in the COA at Kansas State University, there is a small group who did experience this. These negative emotions and feelings due to diversity experiences could likely be the result of the low levels of discussion and interactions with diverse students. Therefore, more diversity programming and diverse involvement within courses and workshops has the

potential to decrease these negative emotions and result in a more inclusive college atmosphere for students. It is hoped that greater experiences with diversity will reduce negative responses to diverse interactions over time.

This study has limitations, including the time frame of the study during the COVID-19 pandemic. The results of the study are influenced by the increase in virtual interactions and decrease in face-to-face interaction between instructors and students. The lack of ability to safely interact with others in person due to the COVID-19 pandemic may have influenced the student level of diversity interactions and decreased opportunities for diversity experiences within universities. At the time of this study (Fall 2020), many universities had transitioned school learning and events into a hybrid or online format due to the COVID-19 pandemic. Therefore, it may have been difficult for students to know if they were interacting with someone from a different background than themselves. Additionally, Pagoto et al. (2020) conducted a study during Spring 2020 semester that determined having less interaction and communication with instructors and students had a negative impact on students throughout the pandemic. Thus, future research should examine diversity experiences in the normal (nonvirtual) university setting and compare with results found in this study. In addition, this study had a relatively small response rate, also likely due to the pandemic. These issues must be considered when interpreting the results of the study. Efforts to increase the response rate in future research could provide enhanced results compared to those presented here.

About the Authors: Lonnie Hobbs, Jr. is a PhD student and Research Assistant at Kansas State University. Zelia Z. Wiley is an Assistant Dean and Director of the College of Agriculture Diversity Office at Kansas State University. Raymond Thomas is a PhD student and Research Assistant at Kansas State University. Summer Santillana is a the Diversity Office Program Coordinator in the College of Agriculture at Kansas State University. Andrew Barkley is a Professor and University Distinguished Teaching Scholar at Kansas State University (Corresponding author: barkley@ksu.edu).

Appendix 1: Survey Results for Diversity Experience Questions (*DIVEXP*)

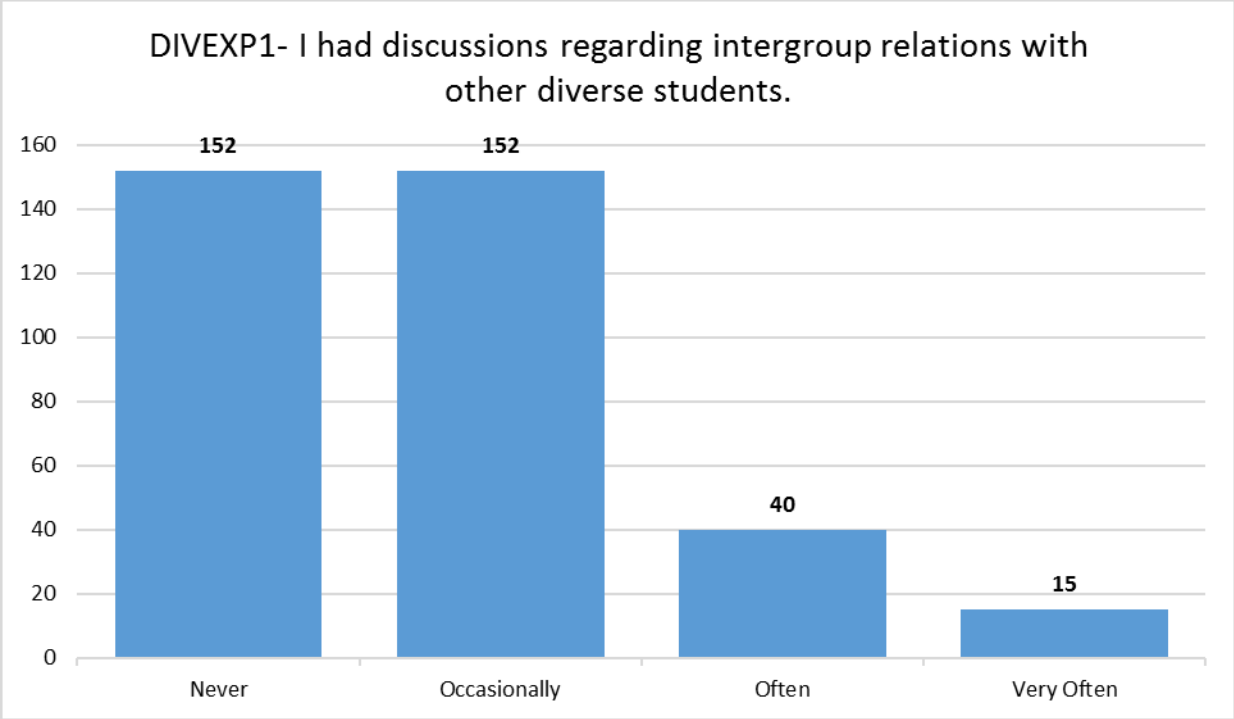

Figure A1: Response Frequency for *DIVEXP1* Variable

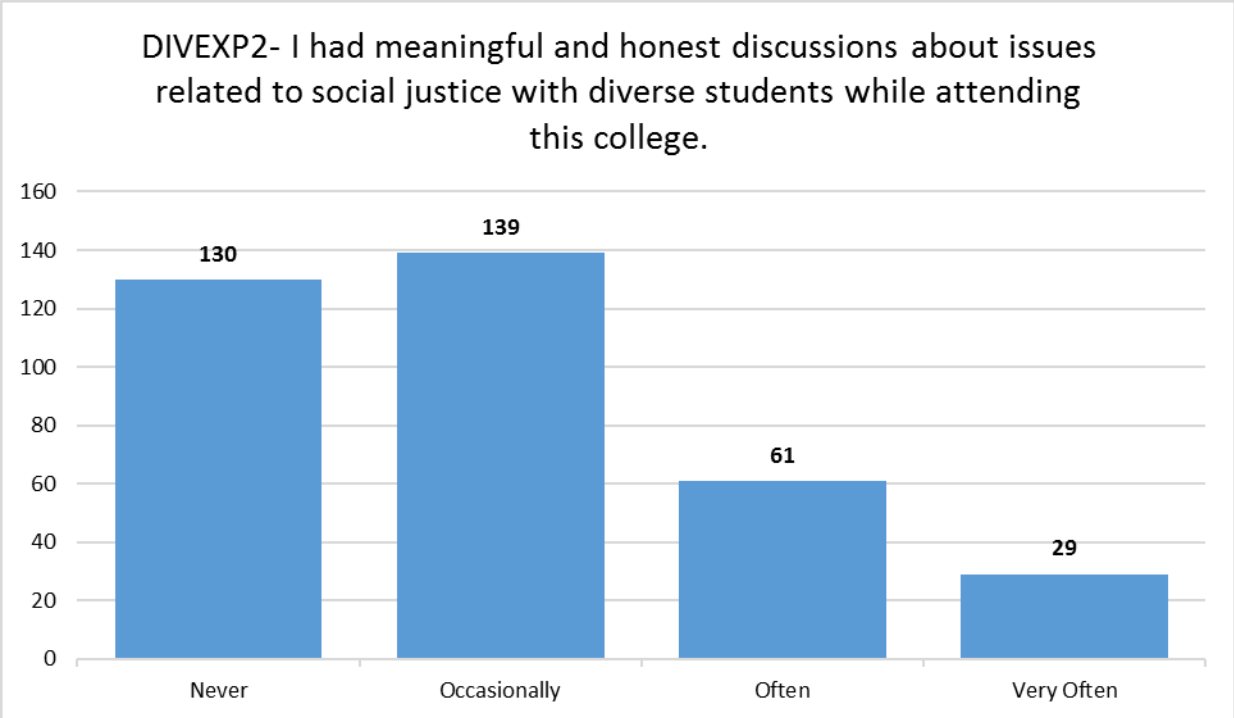

Figure A2: Response Frequency for *DIVEXP2* Variable

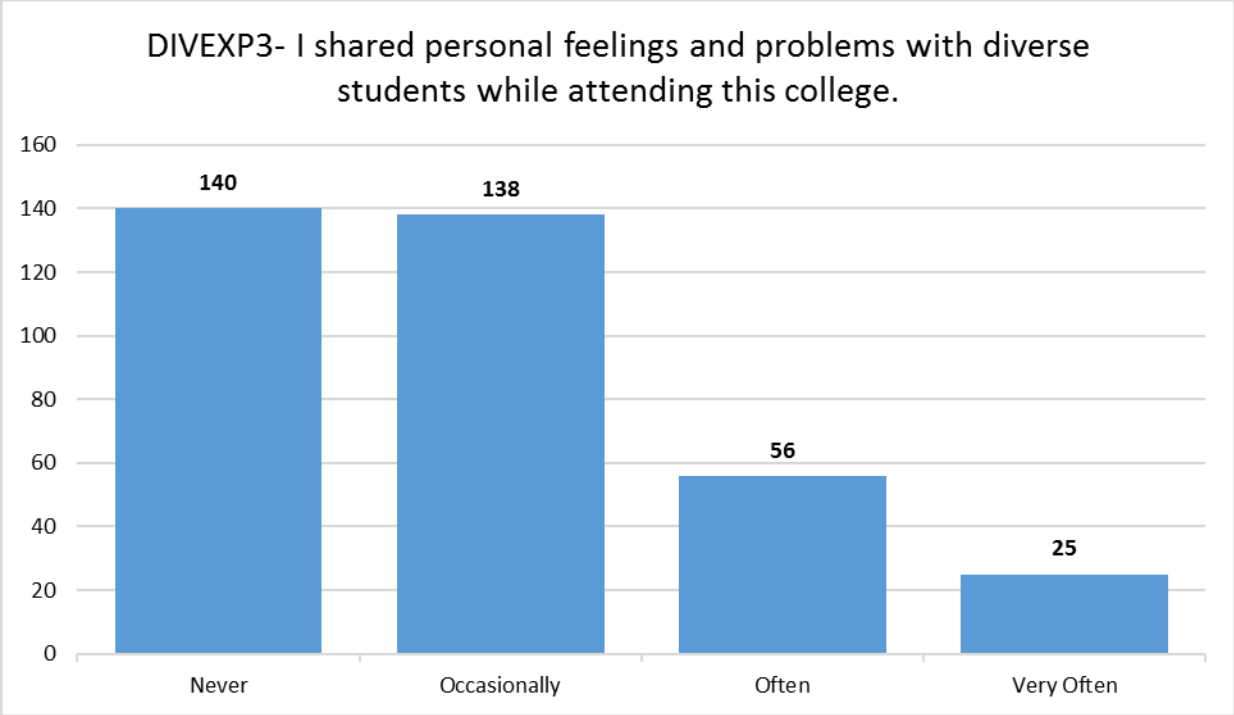

Figure A3: Response Frequency for *DIVEXP3* Variable

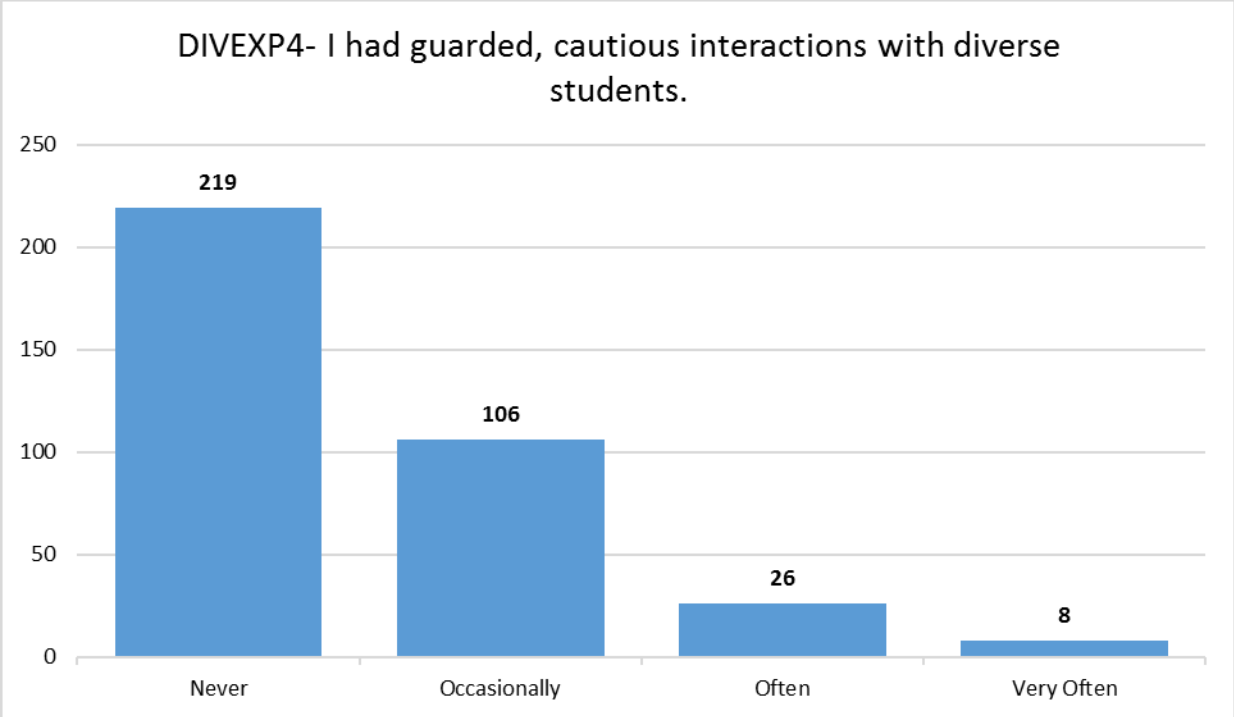

Figure A4: Response Frequency for *DIVEXP4* Variable

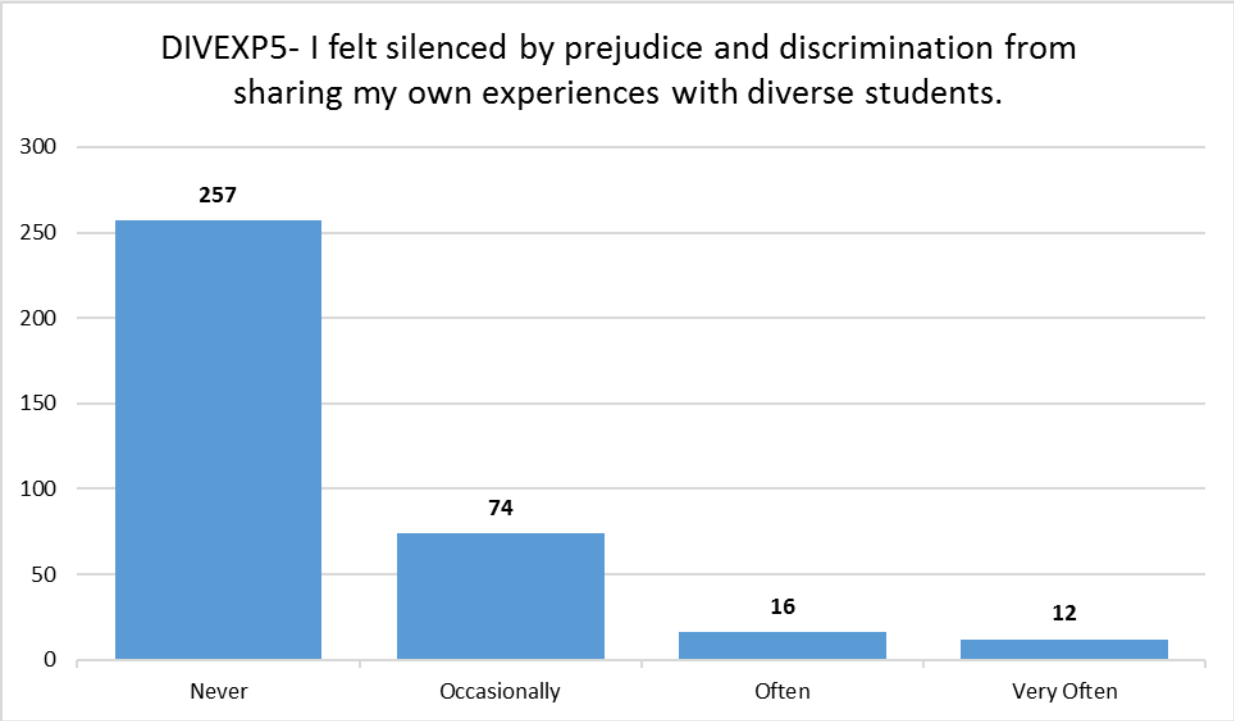

Figure A5: Response Frequency for *DIVEXP5* Variable

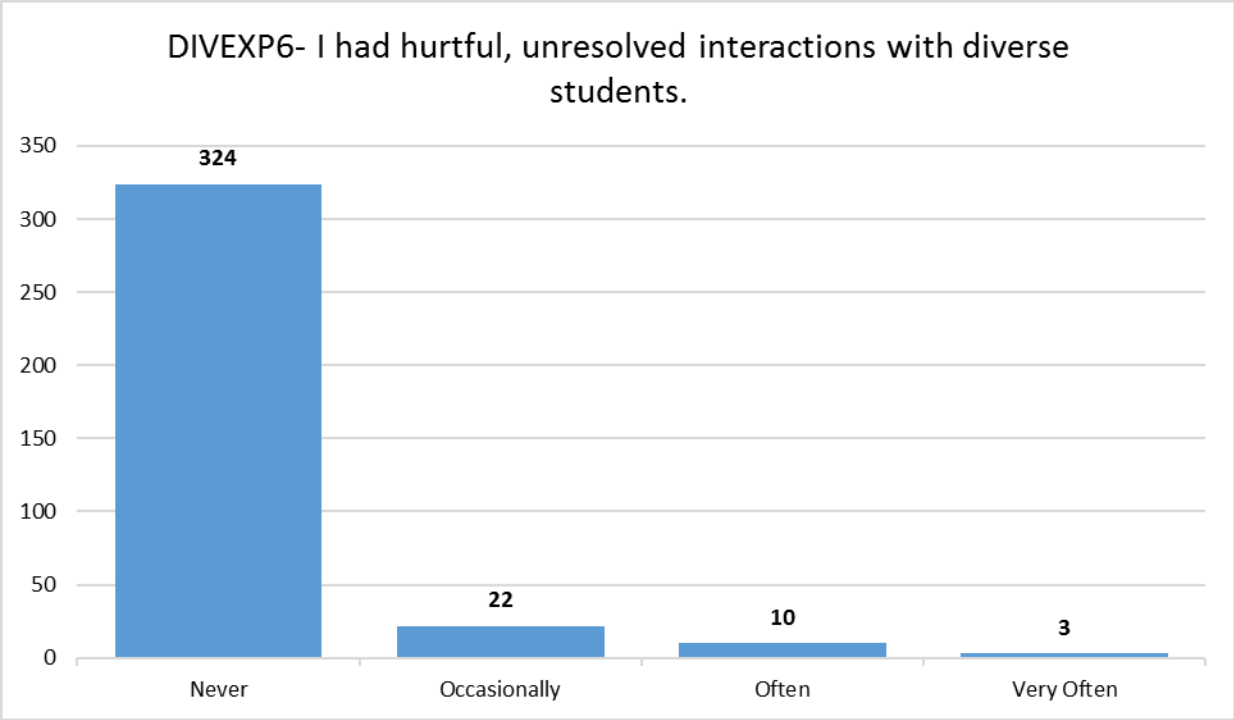

Figure A6: Response Frequency for *DIVEXP6* Variable

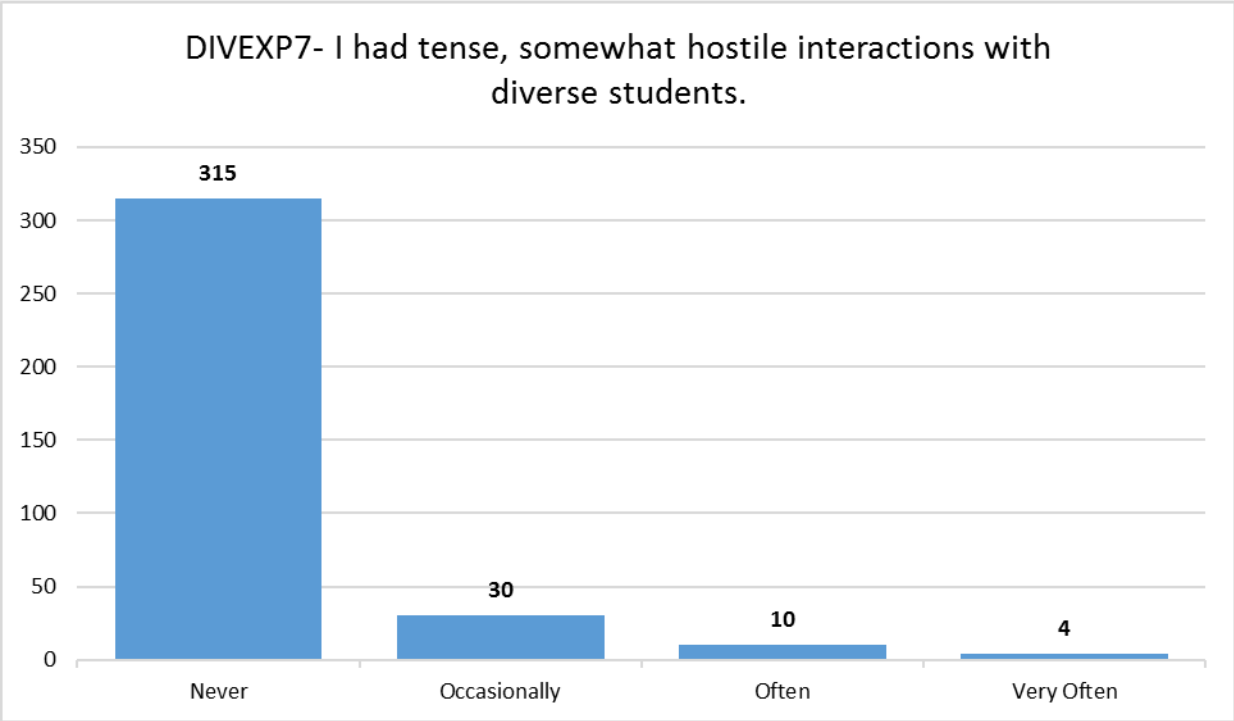

Figure A7: Response Frequency for *DIVEXP7* Variable

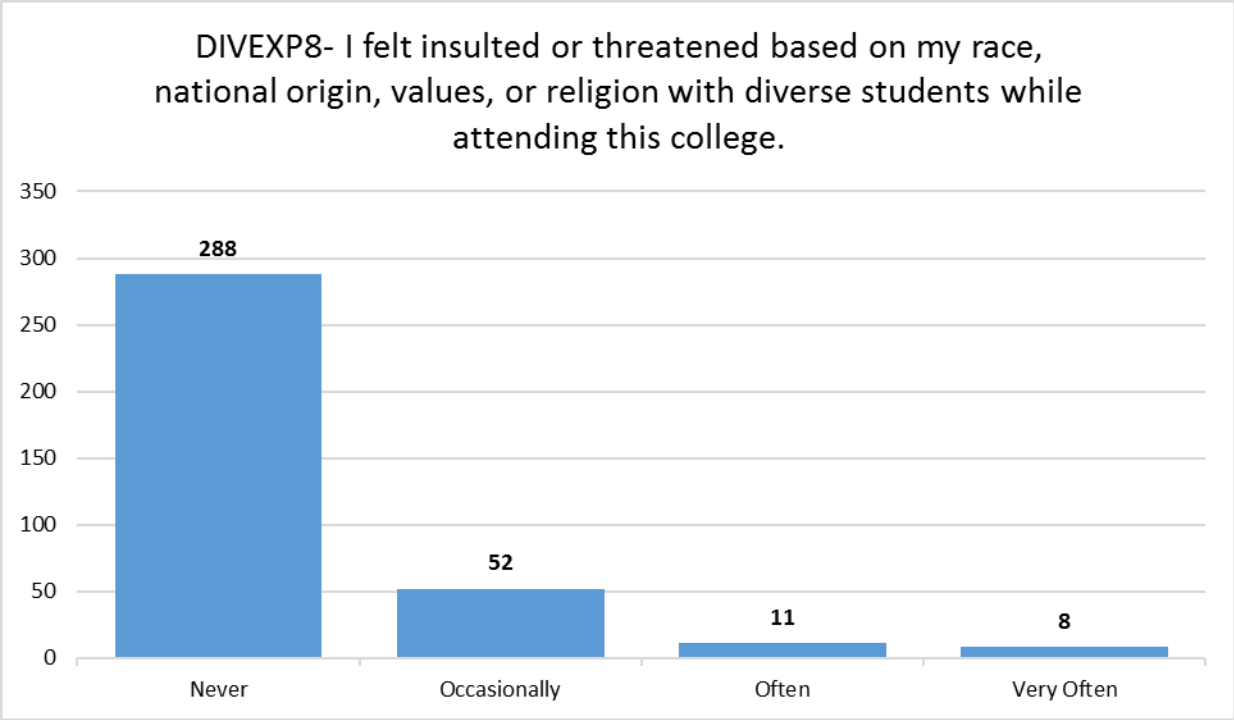

Figure A8: Response Frequency for *DIVEXP8* Variable

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Teaching Commentary

Recommendations for Contextualizing and Facilitating Class Conversations about Diversity, Equity, Inclusion, Belonging, and Social Justice

Donald A. Saucier[a], Noah D. Renken[a], Ashley A. Schiffer[a], and Tucker L. Jones[b]
Kansas State University[a], Washburn University[b]

JEL Codes: A220
Keywords: Conversations, diversity, empathy, engagement, social justice

Abstract
Conversations about diversity, equity, inclusion, belonging (DEIB) and social justice should be incorporated in many courses, but especially undergraduate Agricultural and Applied Economics courses due to their value for students' personal and professional development (e.g., Lambert Snodgrass, Morris, and Acheson 2018; Wiersma-Mosley 2019). However, these conversations present difficulties and challenges that instructors should anticipate and recognize prior to facilitation. To prepare for and maximize these experiences for both students and instructors, we believe instructors should bring PEACE (i.e., *Preparation, Expertise, Authenticity, Caring,* and *Engagement*; Saucier 2019a, 2019b; Saucier and Jones 2020) to the classroom, a framework for modeling and inspiring empathy among their students, and set the foundation for safe, meaningful conversations. In this article, we discuss practical ways instructors can create empathetic and inclusive learning spaces for themselves and their students that allow for conversations about DEIB and social justice issues. We believe our recommendations will increase the utility and success of these conversations in class, which, in turn, will create a more enriching experience for both students and instructors.

1 Introduction

In all courses, including those in Agricultural and Applied Economics, conversations and/or exploration of diversity, equity, inclusion, and belonging (DEIB) are fundamental to students' personal and professional development. Economics can be understood as universal and applicable to every human being (Bartlett 1996), and as such, DEIB and social justice conversations should not be neglected in these classes. In fact, some have argued economists should treat social well-being with the utmost importance, over materialistic values (Piovani and Togrul 2012). Similarly, Pereira and Costa (2019) advocate for stronger ties between undergraduate economics students, the university, and the community due to the implications these relationships have for students' social responsibility.

Unfortunately, though, women and minorities have often been historically excluded from top introductory economics textbooks (e.g., Feiner and Morgan 1987) and continue to be underrepresented among Agricultural and Applied Economics faculty (McCluskey 2019) and in economics (Bayer and Rouse 2016) and agriculture (Thomas, Cotten, and Luedke 1991) professions more broadly. Zepeda and Marchant (1998) argue that we can diversify agricultural economics faculty by attracting and retaining more women and students from marginalized groups during their undergraduate and graduate education through increasing their access to role models and mentoring. Although some courses are explicitly devoted toward addressing social justice in the Agricultural and Applied Economics discipline (e.g., U.S. Food, Social Equity, and Development; Kolodinsky and Tobin 2021), many are not. Further, given the traditionally competitive orientation of business and economics disciplines (e.g., Kimura, Reeves, and Whitaker 2019), students in such fields may at times put a greater emphasis on competition among their peers, rather than inclusion and cooperation. Importantly, students in introductory

economics courses are often diverse in terms of demographic characteristics (e.g., race, gender, socioeconomic status; Bartlett 1996). Plus, diverse economists bring different perspectives regarding economic policy that are consequently important for student learning (Bayer and Rouse 2016). To combat the systemic barriers for underrepresented populations and enhance our students' development, instructors should proactively engage in DEIB conversations within Agricultural and Applied Economics courses.

Given that Agricultural and Applied Economics has been historically led by White men (Charles 2019), it is possible students may not have had conversations about DEIB and social justice in academic settings (or at all), not have truly considered others' perspectives empathetically, or feel defensive. Therefore, more responsibility falls on Agricultural and Applied Economics instructors for embedding DEIB initiatives into their course design and teaching practices. These conversations should aid in students' understanding of others' social experiences, help them recognize inequity around them, and allow them subsequently to choose to be part of the problem or part of the solution for these issues. In this commentary, we discuss practical ways instructors can create empathetic and inclusive learning spaces—for themselves and their students—that allow for conversations about DEIB and social justice issues. While we discuss these recommendations within the context of Agricultural and Applied Economics courses, these recommendations generalize to classes of various sizes, levels, modalities (e.g., face-to-face, online, hybrid), and/or academic disciplines.

2 Why These Conversations Are Difficult

There are several reasons why in-class conversations about DEIB and social justice are difficult for both students and instructors. These topics may not only be difficult to fully comprehend (e.g., some may struggle with understanding the differences between "diversity" and "inclusion"; Roberson 2006), but they may also be sensitive or controversial (e.g., discussing contemporary movements such as Black Lives Matter; Troka and Adedoja 2016). The sharing of differing or even opposing viewpoints, perspectives, and experiences among students may make civil discourse and mutual respect harder to achieve (Shaffer 2019). Further, some students may perceive conversations about DEIB and social justice as personally or professionally irrelevant, especially if students (or instructors) are majority group members. In such situations, students may not feel as if they are allowed to engage in these conversations and may feel threatened or defensive about these topics (Howell et al. 2017). The actual interactions during these conversations may be difficult (e.g., resistance, confrontation, emotional responses; Gayles et al. 2015). Despite these real challenges, literature suggests DEIB initiatives have been considered a growing issue within agricultural education (e.g., Lambert Snodgrass et al. 2018; Wiersma-Mosley 2019), meaning these conversations in our classes are not only important, but necessary.

3 Practical Recommendations for Facilitating Conversations about DEIB and Social Justice

3.1 Set Norms for Yourself as the Instructor

It is important to note that these DEIB initiatives in the classroom, and subsequent conversations, begin with instructors (McNair, Bensimon, and Malcolm-Piqueux 2020), specifically through PEACE, empathy, and trickle-down engagement. "PEACE" is an acronym that describes the persona that instructors may use in their classes: Preparation, Expertise, Authenticity, Caring, and Engagement (Saucier 2019; Saucier and Jones 2020). Though instructors' preparation (Gullason 2009) and expertise (Korte, Lavin, and Davies 2013) are often emphasized in business and economics classes, we argue deliberate displays of authenticity (i.e., instructors' genuine expression of their personality), care (i.e., demonstrating dedication to fostering students' well-being and professional development), and engagement (i.e.,

cognitive, emotional, and behavioral investment in the course) improve the classroom experience for both students and instructors (see Saucier et al. 2022a for more discussion and examples of how to implement PEACE in your class). Similar to PEACE, we also advocate for the infusion of empathy into one's courses.

Empathy refers to one's ability to take the emotional and cognitive perspectives of others (Elliot et al. 2011). We encourage instructors to adopt the empathetic course design perspective as a means to infuse empathy into their classes (see Saucier et al. 2022a for recommendations). Relatedly, inclusive classroom practices (e.g., antihierarchical classroom environments) tend to benefit all students (Hogan and Sathy 2022) and can even motivate social change (Piovani and Togrul 2012). Contrary to the historically competitive nature of business classes (e.g., Pucciarelli and Kaplan 2016), empathetic and inclusive course design has helped us build community, rapport, trust, and connections with our students. Practical demonstrations of this include instructors learning students' names (e.g., Alberts, Hazen, and Theobald 2010), explicitly telling and showing students they care about them and their learning (e.g., Bondy et al. 2007), and sharing their own stories about who they are as people with their students (e.g., Rasmussen and Mishna 2008). Students need to relate to and trust their instructors (Cavanagh et al. 2018) because those who do not may be uncomfortable listening to our, or sharing their own perspectives (e.g., Holley and Steiner 2005).

As instructors establish trust and rapport with students, instructors must be mindful of, and acknowledge, their role in leading DEIB initiatives and conversations (e.g., Keith et al. 2007). In our experience, one of the best practices to facilitate student engagement (related to DEIB initiatives and beyond) is through "trickle-down engagement" (TDE; Saucier 2019b; Saucier et al. 2022b). That is, instructors' engagement in their own courses initiates students' engagement and subsequent learning. In other words, instructors' mindfulness, tone, approach, and empathy in DEIB conversations will likely be modeled by students as well. Ultimately, by establishing PEACE, demonstrating empathy and inclusivity, and modeling engagement, the relationships between you and your students as well as among students will benefit. These relationships are the foundation for positively and productively engaging in conversations about DEIB and social justice and should be established prior to said conversations.

3.2 Define and Clarify DEIB Concepts

To effectively engage in DEIB initiatives and conversations with your students, you should clearly define its components. This is perhaps especially true in Agricultural and Applied Economics courses, given the historic underrepresentation of minority group identities within this field (Feiner and Morgan 1987; Bayer and Rouse 2016; McCluskey 2019). That is, students with majority-group identities may have a different understanding of these terms than students with minority-group identities, and clear definitions of the following terms should be provided by the instructor. Simply, "diversity" refers to human differences (e.g., Van Ewijk 2011), "equity" refers to fairness (Zollers, Albert, and Cochran-Smith 2000), and "inclusion" and "social justice" further the idea that everyone, regardless of their ethnicity, gender, sexual orientation, ability, or any other identity, deserves to belong and be supported (Torres-Harding et al. 2014). Clarify that these terms and concepts like "diversity," "equity," "inclusion," and "social justice" refer to *everyone*. This may be a revelation for some students, especially those with majority-group identities.

3.3 Demonstrate the Value of DEIB in Your Class

The first DEIB-related norm you should convey to your students is that you value DEIB. You can do this before the semester even starts with DEIB-specific syllabus statements (see Hogan and Sathy 2022 for examples). Once the semester starts, you can promote critical thinking about social justice by analyzing race and gender in in-class activities or examples (see Bartlett 1996 for specific examples in both

macroeconomics and microeconomics courses). Another option to promote representation within your Agricultural and Applied Economics classes is to incorporate the work of diverse scholars, which can increase students' sense of belonging within the field broadly (Schinske et al. 2016) and within your class specifically. In accord with Schinske et al. (2016), we recommend consulting the Scientist Spotlights Initiative (https://scientistspotlights.org/) to identify pioneers within the fields of agriculture and economics. As Goering et al. (2022) suggest, Scientist Spotlights can be either student-created (e.g., students identify such scholars) or instructor-created (e.g., instructors provide media resources, like podcasts or TED talks, by these scholars for students to reflect on). These types of activities and reflections provide students with opportunities to better understand various social identities within the context of their discipline and will help prepare them for in-class conversations about these topics.

3.4 Set DEIB Conversation Norms

Again, consistent with TDE (Saucier 2019b; Saucier et al. 2022b), instructors should model behaviors they expect to see in their students, like active listening and respect for others' perspectives and experiences (Jennings and Greenberg 2009). Further, they can set "rules" for their students about how to engage in these conversations (see Howe and Abedin 2013 for recommendations). In our classes, one rule that we state (both verbally and written in our syllabi as a course policy) is that, "No one, including us, may intentionally offend another member of the class." If someone is offended, then we should default to thinking the offense was unintentional. Another rule is that if someone is offended, they address their offense to us as instructors, rather than directly confronting another student, for example. In our experience, this rule allows us to mediate the conversation between students while allowing them to express their feelings, acknowledge each other's perspectives, and retract or rephrase their statements.

We also recommend instructors use "trigger warnings" (i.e., signals to inform students of content that may lead to harmful experiences; Lockhart 2016) to cognitively and emotionally prepare students for the upcoming conversation. We acknowledge that some argue against the use of trigger warnings because they may prevent students from developing effective coping strategies and/or increase their levels of anxiety related to distressing content (e.g., Lukianhoff and Haidt 2018). However, others argue there are benefits to using trigger warnings in class (e.g., creating more inclusive learning environments for students with trauma; see Lockhart 2016), and we recommend them based on our experiences.

3.5 Empower Students' Voices

Many scholars believe students' voices can be a catalyst for inclusive, social change (e.g., Housee 2012; Messiou 2019). In the classroom, this often starts with students sharing their experiences and perspectives, which can happen during reflections or journal assignments that can serve as the foundation for class conversations (see Hackman 2005 for the importance of personal reflection). It is important to note, though, that instructors should not require students to share experiences they are not willing to share, nor should they use any single student's experience to generalize to a larger demographic group (i.e., tokenization; Wingfield and Wingfield 2014). Providing students with the opportunity to use their voices to share and discuss their experiences is a powerful way to help the entire class connect personally with each other, and to the conversation topics.

To continue to hear students' voices, it is important to *validate* students' contributions, especially within the context of having difficult, DEIB conversations. Sharing personal experiences related to DEIB issues is an inherently vulnerable experience for students, and instructors should be intentional in their responses to students' comments and questions. One of the easiest ways to do this is for instructors to verbally thank students for sharing their experiences with the class. Instructors should also demonstrate (and model) active listening skills during DEIB conversations, for example, by paraphrasing students' responses and reflecting students' feelings (see Bodie et al. 2015). Beyond verbal behaviors, instructors

should reinforce their active listening through nonverbal behaviors like nodding, maintaining eye contact with students, and physically positioning themselves toward students who are responding in class (Bodie et al. 2015). These verbal and nonverbal behaviors help validate students' contributions, in our experience.

3.6 Focus on Conversation, not Accusation

Conversations about DEIB and social justice have the potential to be contentious. Importantly, we recommend instructors anticipate and proactively frame these dialogues as conversations rather than debates. In our experience, debates can involve opinions that have similar levels of veracity and possibilities for truth. Debates also often have winners and losers, which is likely not a productive classroom method (Piovani and Togrul 2012). The goal in conversations about DEIB and social justice is not to win, not to identify right and wrong sides, nor to assign blame. Contributions can be acknowledged, and respect can be given, even when parties disagree.

It is possible, if not likely, that at some point in DEIB conversations, students will use incorrect language unknowingly. Rather than assigning blame when students make comments that are inconsistent with the concepts of DEIB and social justice, we encourage instructors to treat these as teachable moments whenever possible to affirm these concepts. In such situations, we tend to use language as follows, "Instead of using that term, the term [insert more appropriate term] better reflects [insert the concept the student was referring to]," which tends to be well-received by students in our experience. It is important for instructors to realize that confrontation comes with cost—calling students out for prejudiced comments may alienate or anger the students, but it is sometimes necessary. For instance, if following up an inappropriate comment with a subtle suggestion to rephrase their comment is unsuccessful, it may be necessary to label the comment clearly and directly as inappropriate (e.g., "That comment may be perceived as offensive to some, and I'm going to ask that you use different language going forward."). Fortunately, we have not experienced the latter situation often, perhaps because of the classroom and conversation norms we intentionally create. Further, instructors should understand that their silence in response to an offensive statement may imply tacit agreement. Overall, in our experience, when students engage with the topics with thought and empathy, and are not intentionally offending others, conversations will be more productive.

4 Caveats

Conversations about DEIB and social justice are valuable, and processing these topics takes time, effort, energy, and emotion (see Griffin and Ouellett 2007). While our recommendations may increase the chances of successful conversation, these recommendations lower, but do not eliminate, the chances that these conversations may appear to go poorly. Discomfort, awkwardness, and even conflict are inevitable to some degree in these conversations, and instructors should also understand that they or their students may make mistakes during these conversations. It is important that, in the context of community and rapport that provided the foundation for their conversations, instructors and students own and learn from their mistakes. Again, we should try to decolonize the curriculum (Charles 2019), which starts with instructors' reflection (e.g., about their own identities, about their discipline) and willingness to guide students through these conversations (McNair et al. 2020).

5 Conclusion

We acknowledge class conversations about DEIB and social justice may be difficult, particularly in Agricultural and Applied Economics classes. However, the challenges these conversations present can and should be anticipated. We advocate for having these conversations because they are worthwhile for students' personal and professional development. Beyond reframing undergraduate (agricultural) economics courses to recruit more women and minority students (see Bayer and Rouse 2016 for specific

tips), we must facilitate conversations about these topics mindfully and empathetically to promote social responsibility and change. To do this, instructors should bring PEACE to these conversations, inspire empathy among their students, and model the norms of engagement to ultimately set the context for safer and more meaningful conversations. We emphasize how easy it is to implement these changes and the value of starting small, like Goering et al. (2022) recommends. And as research consistently demonstrates, these inclusive changes tend to benefit *all* students, not just students from underrepresented groups (Hogan and Sathy 2022). These overarching perspectives and our practical recommendations will increase the success and value of these conversations for both instructors and students.

About the Authors: Donald Saucier is a Professor of Psychological Sciences and a University Distinguished Teaching Scholar at Kansas State University (Corresponding author: saucier@ksu.edu). Noah D. Renken is a Ph.D. Student at Kansas State University. Ashley A. Schiffer is a Ph.D. Student at Kansas State University. Tucker L. Jones is an Assistant Professor at Washburn University.

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Teaching and Educational Methods

Implementing Theory-Based Mentoring and Experiential Learning to Ease Undergraduate Multicultural Scholarship Recipients Transition from Community Colleges to a Large Research Institution

Jaclyn D. Kropp[a] and Danielle Shu[a]
University of Florida[a]

JEL Codes: A20, A22
Keywords: Diversity, Experiential Learning, Inclusion, Mentoring, Scholarship, Transfer Students

Abstract
The U.S. Department of Agriculture provides competitive grants to higher education institutions to support students from diverse backgrounds through scholarships, mentorship, and experiential learning opportunities. The Food and Resource Economics Department (FRE) at the University of Florida was recently awarded one of these grants. In this article, we discuss the theories utilized to develop the multidimensional mentoring and experiential learning programming aspects of FRE's Multicultural Scholar Program. Programmatic aspects were designed to ease the transition of multicultural scholarship recipients transferring from Associate of Arts (A.A.) programs at state and community colleges to a large research institution. We also highlight challenges and successes we faced in implementing the program. We share our experiences such that other agricultural economics programs seeking funding to support multicultural students and developing mentoring programs for multicultural transfer students aimed at increasing diversity and inclusion can learn from our successes and challenges.

1 Introduction

Approximately 42 percent of the nearly 60,000 projected annual jobs openings in food, agriculture, and related fields for graduates with bachelor's or higher degrees are expected to be in management and business (Fernandez et al. 2020). To help meet this need, the Food and Resource Economics (FRE) Department at the University of Florida (UF) recently received a competitive Higher Education Multicultural Scholars Program (MSP) grant from the U.S. Department of Agriculture (USDA; n.d.). Leveraging FRE's strong bachelor's program with individualized mentorship and student engagement in supplemental experiential learning (SEL) opportunities, FRE's MSP aims to increase the diversity of FRE and, ultimately, the agricultural workforce by preparing scholarship recipients in agricultural and applied economics.

Historically, UF, the College of Agriculture and Life Sciences (CALS), and FRE attract a diverse set of students (Table 1), with many Hispanic students coming from South Florida and Central and South America. However, Table 1 shows a recent decline in FRE's enrollment and a slight decrease in diversity among the department's recent graduates. Although the percentage of white students enrolled in FRE has remained consistent, the percentage of FRE graduates that are white has increased. This suggests nonwhite students have lower retention rates and may take longer to complete their degrees.[1] Qualitative exit-interviews of multicultural FRE seniors and alumni, as well as anonymous survey data, collected from Spring 2021 FRE graduating seniors suggest gaps in student support, particularly

[1] UF does not calculate retention rates or time to degree for transfer students. Since 80 percent of FRE's students are transfer students, accurate retention rates and time to degree data for FRE are unavailable.

mentoring as students transitioned from their Associate of Arts (A.A.) degree institution. Table 1 also shows that while the majority of students enrolled at UF and in CALS (the college where FRE is housed) are female, less than one third of FRE students are female. Thus, the MSP aims to increase the diversity of FRE by awarding ten scholarships and providing individualized, holistic mentorship to transfer students pursuing bachelor's degrees in FRE from underrepresented gender, race, and ethnicity groups with preference given to first-generation college students.

Table 1. Enrollment and Number of Baccalaureate Degrees Awards 2014—2019

	2014–2015			2015–2016			2016–2017			2017–2018			2018–2019		
	UF	CALS	FRE	UF	CALS	FRE	UF	CALS	FRE	UF	CALS	FRE	UF	CALS	FRE
Total Enrolled	32,781	3,638	322	34,002	3,673	293	35,518	3,935	309	36,436	4,102	317	37,527	4,254	285
First-Generation	14%	16%	13%	13%	16%	13%	12%	13%	13%	12%	13%	11%	11%	12%	9%
Female	55%	63%	29%	55%	64%	27%	55%	65%	28%	56%	65%	28%	56%	67%	32%
Race/Ethnicity Unknown	3%	3%	2%	3%	3%	2%	3%	3%	3%	3%	3%	4%	3%	3%	4%
Asian	8%	7%	4%	8%	7%	4%	8%	7%	2%	8%	6%	3%	8%	7%	4%
Black	7%	7%	5%	6%	6%	4%	6%	5%	3%	6%	6%	6%	6%	6%	3%
Hispanic/Latino	20%	17%	21%	21%	19%	18%	21%	19%	17%	21%	20%	15%	22%	20%	17%
Native American/Alaska	0%	1%	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%
Two or More Races	3%	3%	2%	3%	3%	1%	3%	3%	2%	3%	3%	4%	4%	4%	3%
Nonresident Alien	1%	1%	7%	1%	1%	7%	2%	1%	8%	2%	2%	6%	2%	2%	7%
Pacific Islander/Hawaiian	1%	2%	0%	1%	1%	0%	1%	1%	1%	1%	1%	1%	0%	0%	0%
White	58%	60%	58%	57%	60%	61%	56%	61%	63%	55%	60%	62%	54%	59%	62%
Baccalaureate Degrees	8,603	1,111	124	8,451	1,060	113	8,569	1,093	108	9,115	1,154	115	9,965	1,229	122
First-Generation	13%	13%	10%	12%	16%	12%	10%	11%	13%	10%	11%	13%	12%	12%	6%
Female	57%	60%	35%	56%	62%	27%	57%	64%	27%	58%	64%	31%	58%	64%	26%
Race/Ethnicity Unknown	3%	4%	1%	3%	4%	4%	3%	3%	3%	3%	3%	4%	3%	2%	2%
Asian	6%	5%	2%	7%	6%	4%	7%	6%	4%	7%	6%	2%	7%	6%	5%
Black	7%	7%	4%	6%	7%	7%	6%	6%	4%	6%	5%	3%	6%	5%	3%
Hispanic/Latino	19%	16%	23%	20%	18%	20%	21%	19%	19%	21%	19%	18%	22%	20%	11%
Native American/Alaska	0%	1%	0%	0%	1%	2%	0%	0%	0%	0%	0%	1%	0%	0%	0%
Two or More Races	2%	3%	3%	2%	2%	1%	2%	3%	1%	2%	2%	1%	3%	3%	4%
Nonresident Alien	1%	2%	10%	1%	1%	4%	1%	2%	12%	2%	1%	5%	2%	1%	8%
Pacific Islander/Hawaiian	1%	4%	1%	1%	2%	0%	1%	2%	3%	1%	2%	0%	1%	1%	0%
White	59%	59%	56%	59%	60%	58%	59%	59%	55%	58%	63%	66%	57%	61%	66%

This article provides an overview of FRE's MSP and reflects on successes and challenges faced in designing and implementing the program. In addition, we discuss theories at the heart of the MSP programming. While the MSP is unique to FRE, we hope that individuals at peer institutions seeking funding to support multicultural students or developing mentoring programs for multicultural transfer students can learn from our experiences.

The remainder of this article is organized as follows. The next section provides an overview of FRE's MSP. The motivation for the MSP program is discussed in section 3. Section 4 presents a brief overview of the transition and student development theories employed to develop the programming. Section 5 discusses the key activities of the MSP linking these activities to the theories. Section 6 discusses challenges and successes of implementing the program, section 7 presents changes to the program to overcome the challenges, and section 8 concludes.

2 Multicultural Scholars Program Overview

Approximately 80 percent of FRE's undergraduate students transfer into the department after completing their A.A. degree or equivalent coursework. These students primarily transfer from community or state colleges while some join FRE after changing their major. Thus, we are working closely with academic advisors at state and community colleges and other departments at UF to recruit diverse scholars who demonstrate leadership and academic excellence, and are near the completion of their A.A. or equivalent coursework. Thus far, eight of the ten awards have been made. Currently, we are recruiting additional scholars for spring 2023 admission.

Scholarship recipients receive a stipend of $6,500 per year for two years and an additional $2,000 to support a SEL opportunity such as study abroad, faculty-guided research experience, extension internship, or agribusiness internship. In addition to financial support, each scholarship recipient receives mentorship from the MSP coaching team consisting of the project directors and departmental advisor and through the newly implemented departmental peer-mentoring program (Agricultural Mentoring Program, AMP). To recruit additional underrepresented students beyond those receiving scholarships, MSP recipients are required to participate in recruiting events at their high schools and A.A. institutions.

3 Motivation for MSP Programming

The MSP programming is motivated by the need to support transfer students throughout their transition to UF. Many first-generation, minority students experience homesickness, emotional distress, and culture shock due to an absence of mentors/role models, high expectations, familial pressures, and the contrast in cultures between their home and campus communities when transitioning to predominately white, nonurban, land-grant public institutions (McCoy 2014). Students transferring from community college settings to large research universities tend to need more support in their first semester to successfully transition than they typically receive (Townsend and Wilson 2006). This is especially true for minority students. If these students do not receive adequate support, feelings of isolation can occur (Owens et al. 2010).

Therefore, individualized, holistic mentorship,[2] particularly in the first semester, is an important aspect of the MPS program. Individualized transition or bridge programming facilitated by faculty, staff, and students and involvement in ethnic student organizations and multicultural center activities can help acclimate transfer students to campus life (McCoy 2014). For example, black students at Dealali Kobla Community College who received individualized, holistic academic coaching by faculty and academic advisors during their first semester indicated feeling more comfortable, noticed, cared about, needed, and appreciated because they had a personal connection with their coach who celebrated

[2] Holistic mentoring is characterized by mentorship that considers the student's background, life outside of college, and emotions as well academics, during the mentoring process (Luedke 2017).

successes and sympathized with failures (Hathaway 2021). Furthermore, the development of positive mentoring relationships affects the likelihood of students persisting through the transition period and probability of students remaining in college one year after coaching (Robinson and Gahagan 2010; Bettinger and Baker 2011).

Once students have successfully transitioned to the university and developed a sense of belonging, attention can be turned to helping students develop career-ready professional skills and experiences. Participation in out-of-classroom activities such as study abroad, service learning, research, or internships can be life-changing for students (Kuh 2008). With many agricultural economics-related professions requiring an above-average competency in skills such as complex problem solving and critical thinking (Data USA 2020), engagement in these opportunities, often referred to as experiential learning or high impact practices (HIPs), is integral to students' long-term success in the workforce. Involvement in HIPs is positively related to GPA and retention with larger positive effects for students from historically underserved backgrounds (Sandeen 2012). Although first-generation students, transfers, and individuals from underrepresented racial or ethnic minority backgrounds benefit significantly from engagement in HIPs (Finley and McNair 2013), students of color and first-generation students are less likely to engage in these opportunities (McDaniel and Van Jura 2020). Thus, removing barriers that inhibit participation and encouraging engagement in HIPs is an important aspect of the MSP.

4 Theory-Based Mentorship and Engagement in Experiential Learning

Brinkley-Etzkorn and Cherry (2020) provide a comprehensive overview of the evolution and application of theoretical frameworks applied to the study of higher education transfer students. Given that the MSP has several goals, including increasing the diversity of FRE, increasing the retention rate of multicultural students, and increasing engagement of multicultural students in HIPs, applying more than one theory was necessary (see Figure 1). We develop the MSP programming around four theories: Schlossberg's Transition Theory (TT; Goodman, Schlossberg, and Anderson 2006; Barclay 2017), Schlossberg's Theory of Mattering and Marginality (MM; Schlossberg 1989), Astin's Theory of Involvement (TI; Astin 1999), and Sanford's Theory of Challenge and Support (CS; Patton et al. 2006). These theories build on prior theories and highlight the importance of assistance throughout the transition process, need for targeted strategies to develop a sense of belonging and overall resiliency, and need to provide opportunities for professional growth. The relationships between the four theories and their application over the four semesters of the MSP is presented in Figure 2.

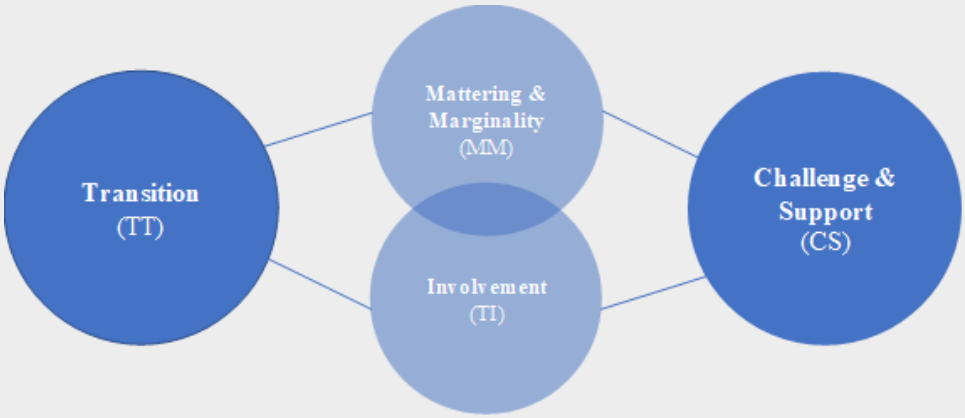


Figure 2: Application of Theories throughout the MSP

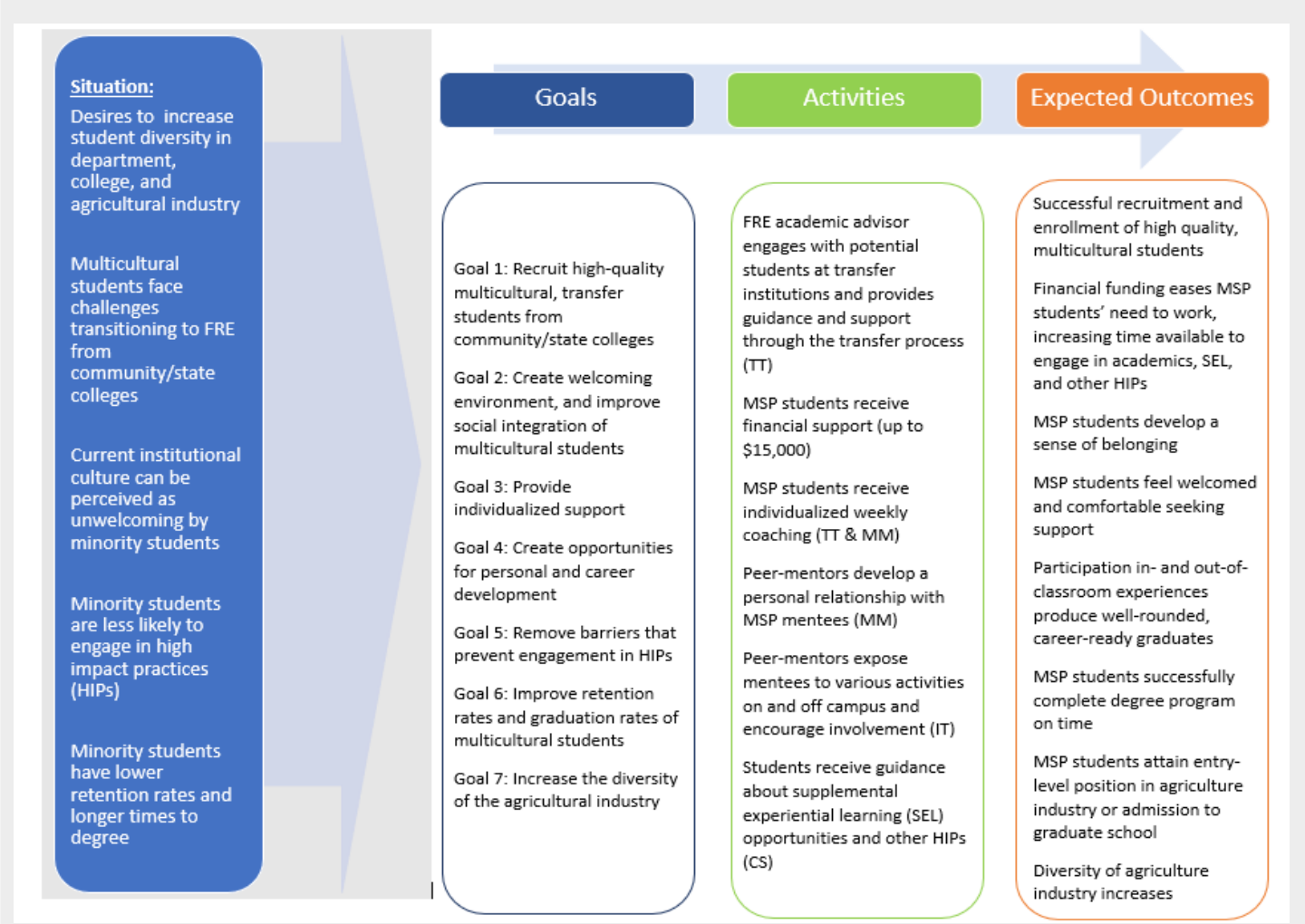
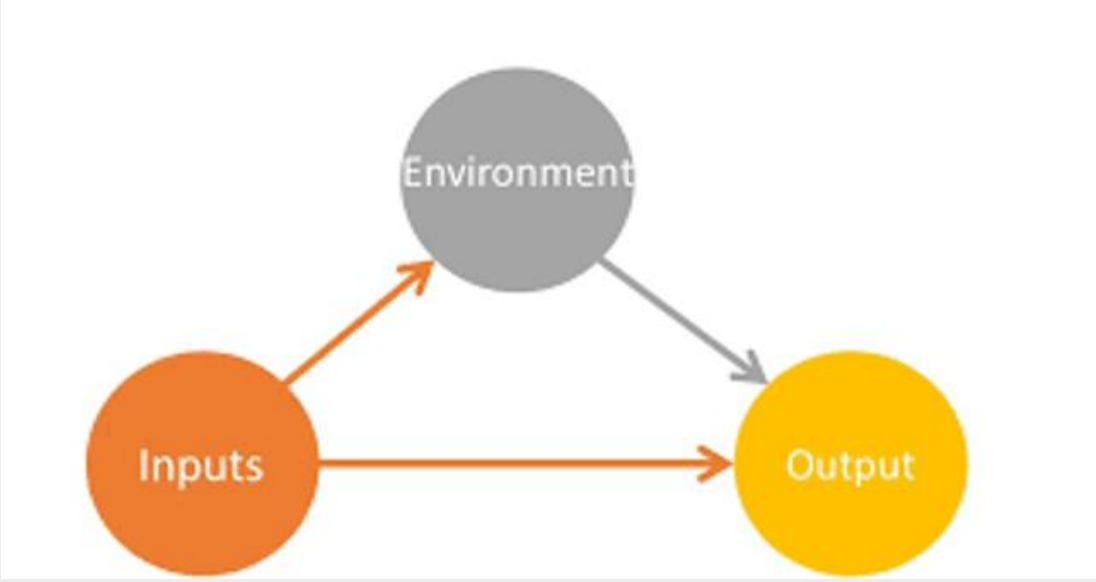


Figure 1: Goals, Activities, and Expected Outcomes of MSP

Schlossberg's TT identifies four factors known as the four S's (Situation, Self, Social Support, and Strategies) that influence a person's ability to cope with a transition. Situation is the assessment of the situation or event that the student is experiencing—in this case, a multicultural student progressing through the admissions process and transferring to UF. Self is the assessment of how the student identifies as well as their level of optimism and ability to handle ambiguity; it highlights the importance of considering the transition from the perspective of the individual student. Support is the external support system, including family, friends, and mentors, available to assist the student in the transition. Strategies are coping resources available to the student including those that the student brings to the transitional experience. The lens of TT has been used to understand the transition of various groups in educational settings including students transitioning from community colleges to larger institutions, male athletes transitioning from community colleges, and adult learners (Flowers, Luzynski, and Zamani-Gallaher 2014; McCoy 2014; Lazarowicz 2015; Burgess and Cisneros 2018; Collom, Biddix, and Svoboda 2021). The first semester of the MSP is grounded in TT. Although support and strategies can vary greatly across students, we developed programming that specifically targets these domains.

Activities early in the MSP program are designed to also incorporate aspects of both Schlossberg's MM and Astin's TI to instill a sense of belonging and promote engagement, respectively. The MSP programing employs all five aspects of MM to create an environment where students feel they matter: (1) providing individualized attention, (2) demonstrating that they are important to us, (3) providing a dependable program, (4) offering opportunities to expand their ego through specific identity groups, and (5) demonstrating appreciation for our students.

Astin (1999) defines involvement as the investment of physical and psychological energy a student devotes to their academic experience. As shown in Figure 3, what students bring with them to college in terms of their characteristics (inputs) and the environment that a student experiences throughout college influences the outcomes (e.g., postgraduation attitudes, beliefs, knowledge, and values). The level of involvement directly impacts what the student gets from the university experience. This suggests engagement in on-campus activities is important for personal and professional development. Hence, these activities are an integral part of the MSP. MM and TI are often combined to provide full support as they are complementary. The previously discussed proactive support intervention at Dealali Kobla Community College is an example of an intervention that combines elements of MM and IT (Hathaway 2021).



Source: Alston, Roberts, and English (2019)

Figure 3: Astin's Theory of Involvement

Sanford's CS states that students grow and develop through experiencing internal or external challenges while also being supported to meet these challenges. This theory has been a centerpiece of designing programming to promote student success for several decades (Upcraft, Gardner, and Barefoot 2005). In a recent mixed-methods study, Longerbeam (2016) finds college environments that facilitate academic success are those with increased opportunities to find support and engage in challenge. Therefore, later in the MSP, while continuing to incorporate aspects of MM and IT, aspects of CS are incorporated to help students seek more advanced opportunities, such as their SEL and other out-of-classroom HIPs.

5 Implementation of Theory-Based MPS Programming

In this section, we discuss key MSP activities and link these activities to the four previously discussed theories. Figure 1 presents a logic model diagram of the MSP that summarizes the goals, activities, and expected outcomes of the MPS and links the key activities of the MSP to the theories.

Using the terminology of Schlossberg's TT, progression of the student's transition occurs into three phases: moving in, moving through, and moving out. During the moving in phase, as the student prepares to transfer to UF, the MSP scholars receive guidance from FRE's academic advisor regarding the admissions process. The MSP scholars also participate in a day-long, university transfer student orientation in which they meet with their advisor, administration, and fellow incoming transfer

students. Moving through incorporates actions taken throughout the student's program, with a focus on activities in the first year, to ensure a successful transition to the university. These activities include the weekly mentoring meetings with the coaches and participation in AMP. We hope that by the moving out phase students have developed a sense of belonging and are ready to tackle challenges such as engaging in their SEL in subsequent semesters and beyond.

5.1 Mentoring from Coaches

As discussed previously, higher education professionals play a vital role in easing the transition and instilling persistence in students. Thus, individualized, holistic mentorship is at the core of MSP programming; MSP recipients are required to attend weekly mentoring meetings throughout the program. The coaching schedule follows a three-week cycle such that each scholar meets with each of the three coaches over the course of a three-week period. The various strengths and skills of coaches creates diversity in perspectives and mentoring approaches. The meetings cover topics essential to the students' long-term success, including goal setting; time management; development of healthy study habits; discussion of available resources in the department, on campus, and in the community; resume writing; stress management; and internship identification. Most of these meetings are one-on-one. Occasionally, the weekly meetings are replaced with group activities such as attending the career showcase or study aboard fair.

Through these weekly meetings and applying TT, the mentors develop an understanding of each scholar's situation and self as a minority student transferring to a larger institution. Luckily, at UF, like many other R-1 intuitions, the structure of independent departments organized into colleges provides a community college feel in a large institutional setting that aids students' transition. During these meetings, we help the scholars identify existing support and strategies (part of the four S's) and introduce them to additional resources. We also consciously implement MM during the meetings. First, we ensure each student receives individualized attention by getting to know them on a personal level and suggesting activities that reflect their career goals and interests. For example, we connected one of the scholars who is interested in local government with opportunities to get involved locally. Next, other aspects of MM are incorporated, including ego extension through forming identity groups with other students in the program.

Prior research suggests the presence of faculty, staff, and other students of color is vital to minority students' acclimation during the transition process (McCoy 2014). Hence, lack of diversity in faculty and administration at primary white institutions can present challenges. Nevertheless, white faculty mentors in cross-race relationships can effectively support minority students and help them develop a sense of belonging (Hathaway 2021). All three members of the MSP coaching team were first-generation college white females with mentorship experience. Understanding the importance of providing positive mentorship, the coaches engaged in additional mentoring trainings prior to the MSP launch to better support multicultural students. The coaches completed the university's Multicultural Mentorship certificate and the Diversity, Equity, Inclusion: Insights into Anti-Racism online course. The project director also completed the semester-long Mentoring Academy offered by CALS that included modules on multicultural mentorship, inclusion, and ethics. Recognizing that most academics do not receive formal mentorship education, the academy was started to create a culture of effective mentoring within CALS. Prior to developing the MSP, the coaches served as university life coaches for first-generation college students and as coaches for academically at-risk students.

5.2 Peer Mentoring

Graduating FRE students frequently indicate during their exit-interviews that they wish they had gotten more involved in campus activities but were unaware of those opportunities or did not know how to get involved. For these reasons, as well as to provide peer-to-peer mentoring for the MSP scholars, AMP was developed. AMP is a peer-to-peer mentoring program that pairs incoming FRE students with continuing FRE students. Students are paired based on a variety of factors including career and graduate school aspirations, personality traits, hobbies, hometown, and demographic characteristics. AMP is a voluntary, department-wide program open to all students; however, MSP scholars are required to participate either as a mentee or mentor each semester that they are enrolled. AMP was first launched in Fall 2021 with nine sets of mentee-mentor pairs. Its framework of student leadership decreases the burden on FRE faculty and staff and ensures AMP will continue after the MSP award period ends. Past mentees are encouraged to become mentors to provide consistency in the program.

Peer mentors participate in a formal orientation and training and are given a resource packet that includes conversation starters, mentorship tips, and a detailed campus resource directory. Mentee-mentor pairs are asked to meet one-on-one at least once a month and are encouraged to participate in group activities organized by AMP advisors such as bowling, game nights, and exam reviews. This allows the student to develop an individual relationship with their peer mentor as well as a sense of community with other AMP participants, aspects at the heart of MM.

Peer mentors are encouraged to engage in practices consistent with IT. Transitioning students need guidance when seeking and exploring opportunities for involvement. Through peer mentorship, the mentees are exposed to and encouraged to engage in departmental and university activities such as Ag Econ Club, academic fraternities, and other on- and off-campus activities.

5.3. Supplemental Experiential Learning

As previously noted, HIPs are important for student development; however, minority students often do not engage in these activities. Thus, we intentionally implemented CS to encourage participation in SELs. We provide information regarding these opportunities by accompanying the MSP scholars to the study aboard fair and passing on internship opportunity information, encouraging participation, and writing letters of recommendation. By providing a financial stipend of up to $2,000 per student to support the scholars' SEL, the MSP aims to increase the likelihood of engagement in these activities by removing one of the largest barriers of entry—funding. Students typically engage in their SEL toward the end of their degree program (summer before senior year or third or fourth semester). SEL activities complement FRE's other experiential learning activities in the classroom (i.e., semester-long simulation games) and out of the classroom (i.e., Southern Agricultural Economics Association [SAEA] and Agricultural and Applied Economics Association (AAEA) quiz bowl and National Agri-Marketing Association (NAMA) marketing competition). The coaching team continues to meet with the scholars during their SEL to provide support, troubleshoot challenges, and provide continued encouragement; most students engage in SEL away from campus and therefore do not have their complete support network available to them, making continued support from the coaches even more important.

6 Reflection on Challenges and Successes

In this section, we highlight the challenges and successes experienced in implementing the program.

6.1 Recruitment

Recruitment of nontraditional, minority, low-income students to FRE's full-time, in-residence program can be difficult because competing online programs allow these students more flexibility in balancing their studies with other responsibilities such as employment and family obligations. Often online programs are also more affordable because students can forgo the cost of room and board. In recent years, recruitment of underserved students has become increasingly difficult as many competing

intuitions expanded their online programing during the COVID-19 pandemic while FRE remains an in-residence program requiring in-person classes.

Furthermore, many potential students' preconceptions of the agricultural industry, as well as economics as a major and UF, hinders recruitment efforts. While FRE has a diverse faculty and staff, the current relative lack of diversity in agricultural fields as well as business negatively impacts potential students' interest in the major. Academic advisors throughout the state are also unfamiliar with the career opportunities available to FRE graduates and hence do not encourage their students to consider it. In addition, potential transfer students do not apply to FRE because they think they will not be accepted. Admission into UF as a freshman is extremely competitive; however, students wishing to transfer into FRE simply need to meet the 2.0 GPA requirement and grade requirements in selected courses (economics, statistics, calculus, and accounting).

The COVID-19 pandemic presented additional challenges because recruiting events at many institutions were held online with these events having lower attendance rates than past in-person events. Furthermore, recruiting students online tends to be more challenging. At in-person recruitment fairs we can draw in potential students that are unfamiliar with FRE by approaching them or through attractive signage highlighting the careers of our alumni. The online recruitment fair environment limits such informal interaction, making it harder to engage with students who are unaware of the major.

Other recruitment challenges arose due to the admissions process at UF. We received notification of the grant only a few weeks before UF's deadline for potential transfer students to apply for admission for Fall 2021 semester. By this time, most of the recruiting and transfer fairs at the state and community colleges had already occurred. Furthermore, transfer students must be admitted by UF's Admissions Department. Thus, we encouraged eligible applicants to first apply for admission to UF. We then worked with college administrators to obtain a list of all admitted transfer students who met the scholarship criteria (i.e., U.S. resident, underrepresented gender or ethnicity/race, not previously enrolled in a bachelor's program in agriculture, and minimum GPA) and encouraged these students to apply for the scholarship. Surprisingly, only about 60 percent of the admitted students who met the criteria applied for the scholarship.

6.2 Retention

As discussed above, retaining transfer and multicultural students past their first year is challenging; this is particularly true in recent years due to COVID-19 and the rise in associated mental health issues. During 2020 and spring 2021, most courses at UF as well as those at state and community colleges were offered online. In Fall 2021, UF returned to an in-person format for all courses that were not online offerings prior to the pandemic. The MSP scholars that started in the fall cohort only had one semester of in-person instruction at their state or community college prior to starting at UF. Therefore, these students who would typically use their transfer institution as a stepping stone between high schools and larger institutions did not have the same experiences as students attending prior to the pandemic. Despite efforts to identify high caliber students and provide support throughout the transition process, one MSP scholar struggled with the transition and was dismissed from the MSP.

6.3 Peer Mentoring

Informal decisions with the scholars as well as anonymous surveys of the AMP mentees indicated that AMP successfully exposed students to various opportunities, eased their transition to UF, and provided a sense of community. While peer mentors and mentees were only required to meet during the mentee's first semester, we observed several of these relationships continued. However, the peer-mentoring aspect of the program was not without challenges. Some mentors did not meet with their mentees as often as required (at least once a month), and one mentor never met with their mentee.

6.4 Cohorts

Although not intended, having multiple cohorts of scholarship recipients has been a positive aspect of the program. The MSP students that started in the fall term served as peer mentors of the scholars starting in the spring. One of these mentor-mentee pairs even participated in a study aboard program together this summer.

6.5 Involvement and Engagement

Overall, the current scholars are excelling. The average GPA of scholars continuing in the program was above the average GPA of other FRE students. Four of the scholars completed their SEL requirement already: three completed study aboard programs, and one completed an internship. In addition to engaging in SELs, the scholars have engaged in various activities within the department and across campus, including Ag Econ Club, Quiz Bowl, and academic fraternities. The MSP scholars are also challenging themselves academically with one pursing a CALS Honors Certificate, another starting a combined degree program (starting graduate studies while still an undergraduate), and another applying for a different combined degree program. These students indicated that the support they have received thus far from the coaching team has fueled their desire to continue their education and engage in additional HIPs.

6.6 Feedback

Another positive aspect of the MSP is our ability to allow the scholarship recipients to advocate for their needs and to incorporate feedback to improve the program. At the end of the fall and spring semesters, we request feedback from the scholars regarding the MSP and whether or not it is meeting their personal growth and professional development needs. Overall, the scholars are happy with their experiences so far. However, they indicated that weekly mentoring meetings are burdensome, particularly around midterms and finals.

7 Actions to Overcome the Challenges

In this section, we discuss the measures that we are taking to overcome the previously discussed challenges. Since recruitment was our biggest challenge, we are employing several strategies to increase the applicant pool. In addition to partnering with advisors at state and community colleges with diverse student bodies, we are engaging FRE faculty housed at UF's extension and education centers throughout the state in the recruitment process. We also updated our recruitment materials to highlight job placements of our recent multicultural graduates and lowered the GPA requirement for the scholarship from 3.0 to 2.5. Several excellent multicultural students who were already admitted to FRE and were planning to enroll were ineligible for the scholarship because their GPA fell just short of our original 3.0 requirement. We realized that the previous standard may have been exclusionary for students who were balancing the challenges of completing their A.A. coursework with other responsibilities like supporting themselves financially.

We also made adjustments to the mentoring aspects of the program based on the feedback we received from the scholars. To ensure meaningful experiences for the mentees, we are requiring mentors and mentees to report their peer-mentoring activities each month so that we can intervene and possibly pair mentees with a new mentor if the responsibilities of the mentor are not being fulfilled or the relationship is not working. Given the MSP purpose is to provide support for the multicultural students rather than burden them with additional responsibilities, we reduced the number of mentoring meetings with the coaches to twice per month for scholars in their first semester and once a month for the continuing scholars. The scholars indicated that group mentoring activities such as attending the career fair and study aboard fair were particularly valuable; thus, we added additional group mentoring

activities. We will continue to seek both formal and informal feedback from the MSP scholars to improve their experiences in FRE and the MSP.

8 Conclusion

This article provided an overview of FRE's MSP, highlighting the theories used to develop its programming and reflecting on the successes and challenges of implementing the program. We hope that sharing our experiences will aid others involved in designing programing for multicultural and underrepresented students. While the MSP only launched in Fall 2021 and hence the scholarship recipients have not yet graduated and thus we cannot evaluate the long-term goals of the program, we have already seen positive benefits of the program; the students currently funded by the program are succeeding in and out of the classroom. The early promising results of the program suggest that the coaching, peer mentoring, and experiential learning programs aspects of the program could be replicated at other institutions seeking to increase inclusion and aid the transition of multicultural transfer students. We will continue to evaluate the progress of the MSP scholars to determine if mentorship and engagement in SELs impacts retention and graduation rates.

About the Authors: Jaclyn Kropp is an Associate Professor in the Food and Resource Economics Department at the University of Florida (Corresponding author: jkropp@ufl.edu). She is also the Project Director for the Multicultural Scholars Program within the Food and Resource Economics Department. Danielle Shu is an Academic Assistant in the Food and Resource Economics Department at the University of Florida.

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Research Article

Impacts of Teaching Modality on U.S. COVID-19 Spread in Fall 2020 Semester

Syed Badruddoza[a] and Modhurima Dey Amin[a]
[a]*Texas Tech University*

JEL Codes: A23, I18, I23
Keywords: College, COVID-19, online, teaching modality, United States, university

Abstract
We study the impact of college reopening in fall 2020 on county-level COVID-19 cases and deaths using the information of 1,076 randomly chosen four- and two-year undergraduate degree-granting colleges from the National Center for Education Statistics. These institutions include public, private nonprofit, and for-profit schools from fifty U.S. states and the District of Columbia. We match college and county characteristics using several methods and calculate the average treatment effects of three teaching modalities: in-person, online, and hybrid on COVID-19 outcomes up to 2 months after college reopening. In pairwise comparison, colleges reopened with in-person teaching mode were found to have about 35 percentage points more cases within 15 days of reopening, compared to those that reopened online, and the gap widens over time at a decreasing rate. Death rates follow the pattern with a time lag. However, colleges with hybrid mode reach up to the rates of in-person mode after some time. We also find that greater endowment and student population, bigger class size, and fewer Republican voters in the county are major predictors of choosing remote teaching modes over in-person.

1 Introduction

The COVID-19 pandemic and its containment measures have unprecedentedly affected human health and economic activities (e.g., Atkeson 2020; McKibbin and Fernando 2020). Countries across the world have implemented partial or full business and school closures to mitigate the spread of infection (Di Domenico et al. 2020; Panovska-Griffiths et al. 2020). Many U.S. colleges temporarily closed or switched to online in the spring semester, and over six out of ten colleges reopened in the fall semester with an in-person or a combination of in-person and online teaching plans (Gallagher and Palmer 2020; Picault 2021). College students mainly fall in the age cohort of 18 to 29 years, which has a lower death rate (0.4 percent) from COVID-19 (Wrighton and Lawrence 2020; Goodman et al. 2021), but a greater chance of socialization than other age cohorts. Although colleges have taken different measures—including symptom screening, contact tracing, cleaning and disinfecting, and mandatory mask policies—there is a chance that reopening colleges may spread the virus among faculty and staff serving students, as well as in the region around the college (Hubler and Hartocollis 2020).

Given the substantial risk of spread of infection from college campuses to the community, a policy question is, if and to what extent, switching to a more remote teaching modality helps in controlling communicable diseases. Although the severity of the pandemic somewhat reduced by the end of 2021, a study that analyzes the effect of different teaching modalities may offer directions in similar crises in the future—such as an expansion of a new variant of COVID-19. The current study applies a quasi-experimental approach to find the impacts of teaching modality on infection spread onto the neighboring areas. Intuitively, we match college and county characteristics to find a pair of similar colleges, where one chose in-person and the other online. Then we measure how choosing an in-person mode might have affected COVID-19 cases and deaths in the neighborhood as opposed to choosing an online mode. We perform similar exercises for two other pairs: in-person versus hybrid, and hybrid versus online. Results

provide evidence that college reopening, especially within in-person teaching mode, increases COVID-19 cases and deaths over time.

Most studies so far have looked into the impact of elementary and secondary school closure, optimal reopening plans, and teaching strategy (e.g., Cohen et al. 2020; Di Domenico et al. 2020; Gandolfi 2020; Panovska-Griffiths et al. 2020). Walke, Honein, and Redfield (2020) discuss the possible issues of U.S. college reopening and the prevention measures required on campuses. Some early studies find an aggregated negative effect of school closures on COVID-19 cases and deaths in the community (e.g., Auger et al. 2020; Pan et al. 2020), whereas some others find little to no negative effect (e.g., United Nations Children's Fund 2020; Herby, Jonung, and Hanke 2022). A more granular level study conducted by Chernozhukov, Kasahara, and Schrimpf (2021) shows that in-person opening of K–12 schools relative to that with remote opening is associated with an increase of 5 percentage points in the weekly growth rate of cases. However, remote teaching in colleges may relate to COVID-19 containment more than remote teaching in schools because college students fall into age groups that are more vulnerable to the disease than their younger counterparts (Goodman et al. 2021). In a study close to ours, Andersen et al. (2020) use an event study under a difference-in-difference setting to investigate college openings' association with cell phone-tracked human mobility and COVID-19 cases in the counties of the campuses. Their preliminary results suggest that reopening increased county COVID-19 cases by 1.7 daily per 100,000 county residents, and in-person teaching created greater visits and higher cases during the reopening weeks, but no contribution from online teaching was found. Nevertheless, most of these studies do not consider the fact that the choice of reopening and teaching modality is endogenous to observed cases. One of the assumptions of the difference-in-difference method is that the allocation of intervention was not determined by outcome, which is violated in this case because teaching modalities were often chosen by colleges based on preexisting COVID-19 rates in the region. Moreover, COVID-19 cases can be influenced by required testing during the reopening weeks, and deaths may take longer than 2 weeks to appear in the data. Additionally, there can be other institutions (e.g., K–12 schools) affecting both COVID-19 outcomes and the decision of instructional modalities. Our primary source of identification is that different colleges reopened on different dates, allowing for a clear comparison. We utilize data from various sources, including cell phone mobility data for comprehensive matching, and we use methods that account for multidimensional differences among colleges and reweight the sample based on the college's possibility of selecting an instructional modality.

2 Method

We are interested in finding the effects of teaching modality on two COVID-19 outcomes: (1) new COVID-19 cases reported in the county, and (2) new COVID-19-related deaths in the county. The impact of teaching modality is assessed on county-level outcomes (and not on the college level) because students may spread the virus to nonstudents and immunocompromised people in the community, which is a critical policy concern. First, we specify a simple relationship between college reopening in the fall semester and the outcome as below:

$$Y_i = \text{Intercept} + \alpha \text{T}_i + \text{Controls}_i \times \beta + \text{error}_i \tag{1}$$

where, Y_i is a COVID-19 outcome, $i = 1, \dots, N$ indicate colleges, and T_i is a binary treatment variable that represents teaching modality. We use three specifications of T_i separately: (1) in-person = 1, online = 0; (2) in-person = 1, hybrid = 0; and (3) hybrid = 1, online = 0 for pairwise comparison of teaching modalities. That is, for each of three regressions, we only include the observations with respective teaching modalities. The vector of control variables includes observed college- and county-level covariates such as college endowments or percent of the population who stayed at home, and β is a vector of respective parameters. Our parameter of interest is α, which shows the impact of a mode of

instruction on an outcome variable, for example, whether switching from online to in-person has an impact on the COVID-19 outcomes. The equation above would have been identified if colleges were homogeneous and were randomly assigned a teaching mode (Barnow, Cain, and Goldberger 1981). In practice, the treatment assignment is not random because colleges choose the mode of teaching based on their distance education capacities, observed COVID-19 cases, and many other characteristics. The probability of adopting a teaching modality may vary considerably across colleges. Intuitively, if we could select two colleges with identical institutional and regional features, except one went in-person and the other online, we could measure the difference in COVID-19 outcomes induced by the teaching modality.

There are some other estimation issues. First, many areas had high COVID-19 cases in the spring and summer semesters. Due to the exponential nature of the disease spread, places with more initial cases will experience faster growth. Moreover, teaching modality in the fall semester may depend on existing cases, thus generating a reverse causality. Second, there can be observed and unobserved college and county features that affect both teaching modality and COVID-19 outcomes, creating an omitted variable bias. Third, a measurement error may occur because infections are reported less during the weekend and more on weekdays, and the incubation or survival period varies. In addition, colleges reopening with in-person teaching elements may require mandatory COVID-19 testing, which leads to an increase in the number of cases. Finally, a county may have multiple colleges or K–12 schools that determine the presence of people in the region, which in turn may affect both college teaching modality and COVID-19 spread. We take several measures to address these problems. For instance, we control for cell phone mobility and many observed college and county characteristics, and we use percentage changes of the outcome variables to eliminate college and county-level unobserved temporal fixed effects. We also check the outcomes for up to 2 months and control for the presence of other colleges in a county. Attempts to address other estimation issues are described below.[1]

One source of identification is that different colleges reopened on different dates between July and October 2020. Therefore, we can isolate the effect of reopening on COVID-19 from the aggregate trend. A bigger identification problem is the presence of other colleges, K–12 schools, clubs, churches, and so on in the county that are unobserved in the data. Trips to these areas may affect the disease spread, as well as the selection of college teaching modalities. Thus, omitting the level of crowdedness or trips made in the county will lead to omitted variable bias. We follow Chernozhukov et al. (2021) to address the problem. They used foot traffic in K–12 schools captured by cell phone mobility data to measure if the school is operating in-person (more foot traffic) or online (less foot traffic). Notice that, even if we control for the foot traffic in K–12 schools, we still need to control for the foot traffic in numerous other places to avoid the omitted variable bias, that is, we must add many other variables in the regression model. A parsimonious way to address the issue is to control for the percentage of the county population who stayed home, recorded by their cell phone locations, according to the following logic:

$$\text{Total population} = \text{population at home} + \text{population outside home} \tag{2}$$

$$\text{Population outside home} = \text{foot traffic in colleges} + \text{foot traffic in K12 schools} + \ldots \tag{3}$$

$$\text{Population at home (\%)} = 100 \times \frac{\text{total population} - \text{population outside home}}{\text{total population}} \tag{4}$$

[1] The motivation of addressing the estimation issues is to try our best to make sure that the treatment assignment was, at least statistically, "equally likely" and the estimates are not biased. A randomized placebo-controlled trial would have generated a more accurate estimate. We discuss this limitation in the concluding section.

where, being outside is specified by staying outside the home for longer than 10 minutes.[2] Thus, controlling for the percentage of the population who stayed home benefits the estimation process in many ways because it comprehensively covers people who are running errands, going for a COVID-19 test, going to schools, colleges, and any other places. We give two examples below.

First, if there are multiple colleges in the county, and we do not observe whether the unobserved colleges are in-person or online, cell phone mobility captures the variation. If the unobserved college reopens in-person, average cell phone mobility in the county should increase more than if it reopens online. On the flip side, the percentage of the population staying home will decrease (eq. 4). Then the increase in COVID-19 outcomes will be explained by the percentage of the population staying outside in various places, and will not corrupt the coefficient with the teaching modality for the observed college. Moreover, if the college teaches in-person but follows a strict "closed" campus policy, cell phone mobility captures that as well. Assume two colleges both teaching online, but one has more students returned to campus for an open campus policy. The cell phone mobility controls for the variation in COVID-19 outcomes unexplained by the teaching modality.

Second, Chernozhukov et al. (2021) found a 0.09 correlation between K–12 school visits and college visits during the reopening weeks. Thus, if K–12 school reopening is correlated with college teaching modality, our estimation will be biased. Following Chernozhukov et al. (2021), the reopening of K–12 schools will reflect in their foot traffic, and controlling for cell phone mobility will capture the unobserved variation in COVID-19 outcomes, which allows us to estimate the effect of college teaching modality. Infection rates in neighboring counties will affect a county via population mobility, so a spillover effect will be controlled for as well.

What does the coefficient with the teaching modality variable capture? Assume two comparable colleges in two counties have the same foot traffic, and counties are similar in all other aspects related to COVID-19 and college teaching modalities, both of the colleges have students on campus and similar average cell phone mobility per day, but one of them reopened online and the other in-person. Our estimate gives the difference between COVID-19 cases in two counties generated by the teaching modalities only: the effect of students attending an in-person class as opposed to an online one, holding everything else fixed.

To deal with the heterogeneous starting values of COVID-19, measurement errors (e.g., more testing on weekdays), and threshold selection issues (e.g., incubation period), we use 2-week intervals: 0–15 days after reopening, 15–30 days after, 30–45 days after, and 45–60 days after reopening; and run separate cross-section regressions for each subsample. The 2-week period is selected based on the incubation periods (e.g., Paul and Lorin 2021). The benchmark of percentage calculation is 0–15 days before reopening, for example:

$$\%\text{ change in cases}_{\text{0 to 15 days after reopening}} = 100 \times \frac{\text{cases}_{\text{0 to 15 days after reopening}} - \text{cases}_{\text{0 to 15 days before reopening}}}{\text{cases}_{\text{0 to 15 days before reopening}}} \tag{5}$$

and so on. We chose 2-week intervals because doing so gives COVID-19 enough time to appear in the outcomes, and we did not go beyond 60 days because the effects may be contaminated by other exogenous factors.

[2] Cell phone locations are accurate up to 30 meters on average and are recorded every 10 minutes for 24/7. The percentage of people who went outside home means people who went farther than 30 meters from their night-staying location at any point in 24 hours for longer than 10 minutes. The implicit assumption we make here is at least college students have access to a cell phone device. This is not unrealistic because Pew Research Center (2021) reports that 100 percent of Americans aged 18–29 own a cell phone of some kind. Another assumption is to define fixed night-staying location as home.

More testing will result in more cases. The 15-day interval approach, combined with the cell phone mobility above, helps us isolate the effect of increased COVID-19 testing during reopening weeks in colleges with in-person modes. This is intuitive because (1) testing requirements for college reopening are less likely to go beyond the first month after the semester starts, so a statistically significant α beyond the first 30 days is more likely to represent the contribution of teaching modality, (2) cell phone mobility reflects trips to the testing center as well, hence helps identify α, and (3) COVID-19-related deaths are not affected by testing requirements, and incubation-to-death period may take longer than a month. So a positive significant α for COVID-19-related deaths after 30 days presents a more convincing case.

The next challenge is to ensure the comparability between colleges. We implement various matching methods described below to address this problem. We employ five methods and check if the results are robust: (1) bivariate Ordinary Least Squares (OLS) where $\beta = 0$ in the model above, (2) multivariate OLS where $\beta \neq 0$, (3) propensity score matching (PSM), (4) Nearest Neighbor (NN) matching, and (5) Kernel Multivariate Distance Matching (KMDM). The first two methods are conventional. The latter three methods focus on finding "statistical twins" for each observation in the treatment group from the control group with similar values of the covariates. The average treatment effects can be calculated as the mean of differences between the observed values in the treatment group and the imputed counterfactual values. We present a nontechnical version of the matching methods below.

Rosenbaum and Rubin (1983;1984) discuss PSM to adjust the probabilities for the differences in pretreatment variables. A propensity score is the conditional probability of receiving the treatment given the pretreatment variables, that is, $P(T_i = 1|X_i)$. The probabilities of treatments generated are used to create weights that adjust the pretreatment imbalances. For example, if a college has a high probability of choosing online than in-person, greater weights are assigned to in-person than online during the estimation. PSM is usually calculated using logistic regression. For a recent technical discussion, see Imbens (2000) and McCaffrey et al. (2013).

Although finding a match with PSM is relatively easier, many studies argue that matching with propensity scores can be misleading because it ignores the multidimensional differences between two observations and simplifies them into one dimension—the score (e.g., King and Nielsen 2019). The NN matching adopts a more multidimensional approach and uses some (default being one) closest observations in the control group. In the case of ties, NN uses all ties as matches. Conversely, a single control observation can be used many times with replacement. Matching with more than one continuous covariate may induce bias, so we apply a bias-adjusted NN matching proposed by Abadie and Imbens (2011).

Our final matching technique, KMDM, is similar to NN, but uses a certain bandwidth for multivariate matching instead of comparing with the closest neighbor. Simulation studies show that KMDM tends to outperform PSM because it approximates fully blocked randomization, which is relatively more efficient (King and Nielsen 2019). We apply KMDM where observations in treatment and control groups are matched using Mahalanobis distance, and use the Epanechnikov kernel function to assign larger weights to controls with smaller distances. Following Huber, Lechner, and Steinmayr (2015), we choose 1.5 times the 90 percent quantile of the nonzero distances in finding a pair. The use of KMDM is more appropriate in our case, given the multidimensional heterogeneity among colleges and counties. See Jann (2017) for further discussion on the advantages of KMDM over other methods.

3 Data and Descriptive Statistics

For college characteristics, we utilize the Integrated Postsecondary Education Data System (IPEDS) survey annually released by the National Center for Education Statistics (NCES, 2020). The IPEDS survey includes information on four- and two-year undergraduate degree-granting colleges and universities from all fifty U.S. states and the District of Columbia. Variables include tuition and fees, enrollment,

number of degrees and certificates conferred, number of employees, financial statistics, and so on. More than 6,000 such Title IV institutions (i.e., institutions that process U.S. federal student aid) were listed by the NCES in 2020. These institutions include public, private nonprofit, and private for profit schools that provide postsecondary education or training beyond the high school level. We aimed at selecting a thousand colleges for our analysis and randomly chose 1,100 of them using a random number generator under the uniform distribution. The extra 100 colleges were selected to ensure that dropping missing values did not decrease the sample size below 1,000. Merging this data set with other data sets, as described below, eventually gives 1,076 colleges after dropping the missing observations. Among the selected colleges, 41 percent are public, 42 percent are private nonprofit, and the remaining 17 percent are private for profit.

Data on teaching modality and the official start date of the fall 2020 semester were manually collected between July and December of 2020 by authors from respective college websites.[3] Over 90 percent of the colleges mentioned their latest teaching modality between June and September 2020. Information for the remaining colleges was obtained from contemporary campus news or local news. Some examples of search phrases we used are, "XXX university fall 2020 COVID-19 information reopening plan new" or "XXX college restarts in-person class in fall 2020" or "XXX institute fall 2020 plan president announcement updated." We categorize fall reopening plans into three types: (1) in-person, (2) online, and (3) hybrid. Colleges in the "in-person" group started the fall 2020 semester with face-to-face classes and open residence halls, and may include few online delivery materials; colleges in the "online" group primarily offered online classes with some exceptions for lab components and may have some students on campus; and colleges in the "hybrid" group either divided the class into online and in-person section, or switched the teaching mode on a rolling basis, or offered courses with both in-person and online access. Thus, colleges that changed teaching modalities during the sampled period were considered hybrids. We understand this might create noise in the hybrid category, but we kept the in-person and online categories pure (either fully in-person or fully online), as their difference is the main interest of this research. Moreover, the definition of hybrid substantially varies from one college to another, so it is more convenient to utilize in-person and online modes to infer the effects of hybrid modes than to study all types of hybrid modes. In our sample, 406 colleges (37.73 percent) taught online, 386 (35.87 percent) taught in-person, and the remaining 284 (26.39 percent) followed a hybrid method.

We obtain daily new COVID-19 cases and deaths at the county level from the *New York Times* (2020) to stay consistent and comparable with similar studies conducted before (e.g., Andersen et al. 2020; Fox, Lachmann, and Meyers 2020; Chernozhukov et al. 2021). Moreover, the *New York Times* data and Centers for Disease Control and Prevention data are highly correlated (Chernozhukov et al. 2021). Figure 1 simply plots the changes in COVID-19 cases and deaths as a percent of 15 presemester days grouped by college teaching modality. We took the percentage changes to remove the influence of initial values, and to get rid of the college and county-level idiosyncratic features. Different colleges started the fall 2020 semester on different dates from the end of July to October. The earliest reopening date for the fall semester is July 20th in our sample whereas the latest date is October 24th. Figure 1 matches the reopening dates and suggests that COVID-19 cases were exponentially growing in the fall semester regardless of teaching modality, and COVID-19-related deaths followed the pattern. However, colleges teaching online are located in counties that had slower growth of cases after the college reopening date, on average. Cases were slowly growing for colleges with hybrid teaching modes as opposed to colleges with in-person modes. After 30 days, the pattern of cases is reflected in the pattern of deaths. On average, counties where colleges taught in hybrid or in-person mode had greater COVID-19-related deaths than counties where colleges taught online. However, an econometric analysis is required to find the impact of teaching modality on COVID-19 outcomes.

[3] A list of colleges and their webpages are publicly available in school_info.txt on https://github.com.

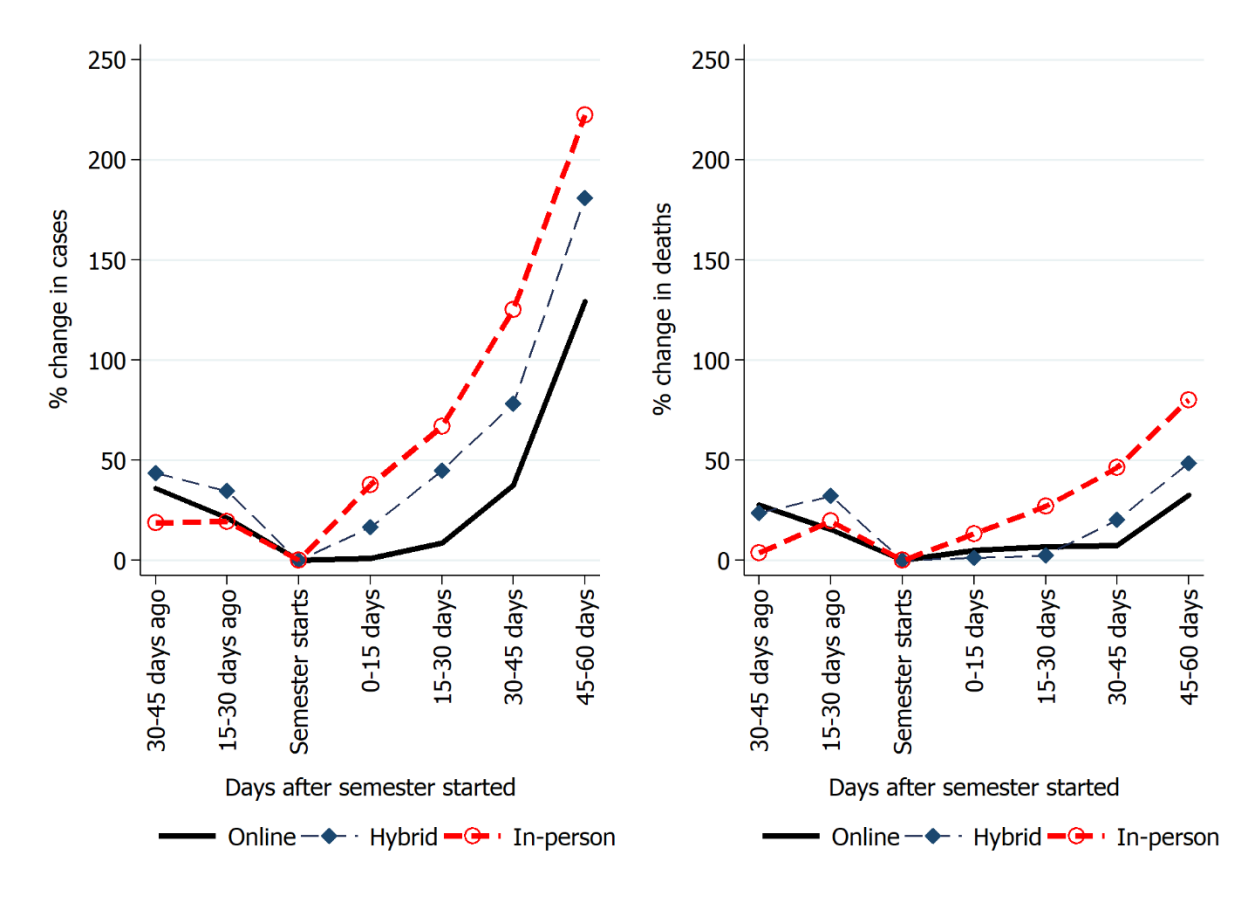

Figure 1. Growth of COVID-19 Cases by College Teaching Modality in Fall 2020 Semester

Note: Figures are averages across colleges. Daily data of 1,076 colleges from July to October 2020. See the data section for details.
Source: COVID-19 outcomes are obtained from the *New York Times* (2020), and teaching modalities were collected by authors from the respective college websites.

We select several control variables for the econometric analysis based on the literature. Table 1 provides variable descriptions and sources, and Table 2 presents summary statistics of variables. As discussed in the method section, one of the most important control variables is the average percentage of the county population that stayed home. We collect this variable from the Bureau of Transportation Statistics (BTS; 2020). The variable records the 7-day moving average of cell phone mobility at the county level, such that "staying home" is defined by cell phones that do not go outside the home for longer than 10 minutes. Intuitively, we get a percentage of the county population that are not home for each 10 minutes, then average the figures to get one number for a day, then calculate the 7-day moving averages. As shown in Table 2, fewer percentages of the county population (24.21 percent) stayed home under the in-person category, compared to hybrid (25.05 percent) and online (26.41 percent). The similar staying home rates across teaching modalities makes the covariate balancing more appropriate. Omitting the stay-home variable makes the effects of a teaching mode on COVID-19 outcomes biased because COVID-19 outcomes may increase if fewer people stay home, given that cell phone mobility is associated with teaching modalities in schools (Chernozhukov et al. 2021).

We include five college-level controls: (1) enrollment, (2) cost of attendance, (3) endowment per student, (4) student-faculty ratio, and (5) public versus private dummy variable. The total enrollment variable controls for the size of the college, which can be an important determinant of disease spread

(e.g., Fox et al. 2020). Endowment per student and cost of attendance, respectively, capture the financial capacity of the college and the average affluence of its students—both are critical determinants of technology adoption in schools (e.g., Brahmasrene and Lee 2012; Leu, Forzani, and Kennedy 2015; Sun and Chen 2016; Gallagher and Palmer 2020). The variable on student-faculty ratio is an indirect measure of the average class size (De Paola, Ponzo, and Scoppa 2013) that may affect both case spread and remote teaching decisions. We also include a binary variable on whether the college is public or not because public colleges can be subject to COVID-19 containment rules and regulations. Moreover, many public schools may have administrative or financial constraints to abruptly change teaching modes. Table 2 indicates that these college characteristics vary across teaching modalities.

Control variables on county characteristics were extracted from the American Community Survey (ACS, 2020). One of the most important variables is the total population, which primarily determines the rate of disease spread (Siedner et al. 2020). We further added the percentage of Black population and the percentage of men in the county to capture their disproportionately higher COVID-19 rates (e.g., Millett et al. 2020; Kim et al. 2021). Real household income controls for the average financial capacity of the county population, including students, to adopt new technologies and deal with income shocks during COVID-19 (e.g., Tan et al. 2021). The binary variable on rural campus is added following the definition of U.S. census because the rural location may affect the capacity and decisions regarding teaching modality. A variable on the existing mask ordinance was also included because mandatory mask mandates were found to have a negative association with case growth (Chernozhukov et al. 2021). Individual mask policies in county and state were obtained from HealthData.gov (2020). For some states, decisions regarding public university reopening were determined by central agencies, so we include state fixed effects in all models.

We also added information on county-level shares of Republican votes in Presidential Election 2016 from the MIT Election Data and Science Lab (2018) to take residents' perception of COVID-19 risk into account (e.g., Tyson 2020). Two other critical county-specific variables are COVID-19 cases and deaths in the spring 2020 semester because it was the last regular semester that gave the college administration a signal about the disease situation in the community. Higher cases and deaths in spring while the campus was open may influence college administrations to switch to online teaching modes (Gallagher and Palmer 2020). Some studies find an association between temperature and COVID-19 spread (e.g., Livadiotis 2020), so the average temperature in the county during the reopening month was included in the model from the National Oceanic and Atmospheric Administration (NOAA) data (National Centers for Environmental Information 2021). Finally, the total number of colleges in the respective county (including the sampled college) was included in the regression from NCES data to remove the spillover effects, that is, the contribution of other colleges to COVID-19 outcomes. We admit that the data may not include all offices and institutions that may affect both COVID-19 cases and teaching modality, but controlling for cell phone mobility together with college count and other identification strategies above should isolate the influence of relevant institutes from our analysis.

A required condition for estimating treatment effects is distributional similarities of pretreatment covariates across the treatment groups (McCaffrey et al. 2013). Table 2 indicates considerable variation across teaching groups. The difference justifies the use of matching in our analysis. Tests for the distributional equality of matching variables between the treatment and control groups are placed in the appendix (see Figure A1). For PSM, these control variables are used to find the determinants of teaching modality using logistic regressions. The matching process should only contain variables that are measured at baseline because variables measured at around the treatment may be influenced or modified by treatment (Austin 2011). Therefore, we selected the determinants from the latest academic year available before fall 2020 semester.

Table 1. Variable Description

(1) Variable	(2) Unit	(3) Source	(4) Details
Online	Binary	College websites	Takes 1 if the college holds classes primarily online for fall 2020, zero otherwise
Hybrid	Binary	College websites	Takes 1 if the college adopts a combination of online and in-person modes for fall 2020, zero otherwise
In-person	Binary	College websites	Takes 1 if the college holds classes primarily in-person for fall 2020, zero otherwise
New cases	Numeric	*New York Times* (2020)	Daily new COVID-19 cases per 100,000 population in the county
New deaths	Numeric	*New York Times* (2020)	Daily new COVID-19 deaths per 100,000 population in the county
% stayed home	Percentage	BTS (2020)	Percentage of county population that did not go outside home for longer than 10 minutes
Enrollment	Count	NCES (2020)	Total student count in fall 2018 semester, including graduate and remote students
Cost of attendance	USD	NCES (2020)	Total price for in-state students living on campus for 2019–2020
Endowment per student	USD	NCES (2020)	Endowment assets per full-time equivalent enrollment at the end of 2018
Student-faculty ratio	Ratio	NCES (2020)	Enrollment divided by total full-time instructional staff
Public	Binary	NCES (2020)	Takes 1 if the institution is primarily funded by a state government, zero otherwise
Total population	Count	ACS (2020)	Total population in the county where the college is located (2018)
Black population	Percentage	ACS (2020)	Percentage of African American population in the county (2018)
Male population	Percentage	ACS (2020)	Percentage of male population in the county (2018)
Rural campus	Binary	College websites	Takes 1 if the college has a rural campus by 2010 census definition, zero otherwise
Household income	USD	ACS (2020)	Median real household income in 2018
Republican votes	Percentage	MIT Election Data and Science Lab (2018)	Percentage of votes for the Republican Party at the county level in the 2016 Presidential election
Mask ordinance	Binary	HealthData.gov (2020)	The county has an ongoing mandatory mask policy for individuals in public places
Cases in spring 2020	Count	*New York Times* (2020)	Total COVID-19 cases in the county by May 15, 2020
Deaths in spring 2020	Count	*New York Times* (2020)	Total COVID-19 deaths in the county by May 15, 2020
Temperature	Fahrenheit	NOAA (2021)	County mean temperature in reopening month
County college count	Count	NCES (2020)	Number of colleges listed in the NCES data

Note: Means and standard deviations of the variables are placed in Table 2.

Table 2. Summary Statistics

(1) Variable	(2) Online	(3) Hybrid	(4) In-person	(5) Overall
Daily new cases	247.00	100.04	72.43	145.59
	(558.23)	(282.69)	(248.92)	(408.97)
Daily new deaths	4.12	1.62	1.09	2.38
	(10.54)	(5.98)	(4.39)	(7.75)
Online				0.38
				(0.48)
Hybrid				0.26
				(0.44)
In-person				0.36
				(0.48)
% stayed home	26.41	25.05	24.21	25.27
	(4.06)	(4.33)	(4.00)	(4.22)
Enrollment	8,828.61	6,307.21	4,417.95	6,580.85
	(9,991.36)	(8,272.99)	(6,972.39)	(8,754.75)
Cost of attendance	44,980.83	46,178.28	41,089.31	43,757.31
	(21,312.56)	(19,431.71)	(16,628.42)	(19,059.39)
Endowment per student	61,279.10	28,545.41	59,892.61	51,811.22
	(347,471.23)	(62,887.43)	(367,714.37)	(307,016.55)
Student-faculty ratio	41.71	28.11	29.18	33.61
	(30.23)	(22.71)	(25.53)	(27.44)
Public	0.60	0.38	0.33	0.44
	(0.49)	(0.49)	(0.47)	(0.50)
Total population	1,578,217	616,050	444,525	917,566
	(2,620,932)	(973,588)	(1,028,931)	(1,867,046)
Black population	14.57	13.68	11.89	13.37
	(15.77)	(14.44)	(13.14)	(14.55)
Male population	49.13	49.13	49.14	49.14
	(1.28)	(1.19)	(1.27)	(1.26)
Household income	64,587.54	59,805.99	56,796.75	60,526.88
	(17,710.66)	(15,156.93)	(14,395.72)	(16,253.30)
Republican votes	38.94	46.09	52.97	45.86
	(16.72)	(16.25)	(14.53)	(16.93)
Mask ordinance	0.86	0.80	0.71	0.79
	(0.35)	(0.40)	(0.45)	(0.41)
Rural campus	0.16	0.22	0.35	0.24
	(0.37)	(0.41)	(0.48)	(0.43)
Cases in spring 2020	12,706.16	5,356.90	3,576.15	7,498.42
	(23,007.05)	(10,396.52)	(10,177.45)	(16,800.38)
Deaths in spring 2020	594.02	288.29	70.89	370.25
	(1,038.35)	(568.51)	(5.298)	(789.65)
Temperature (F) in reopening month	72.37	71.38	70.89	71.58
	(6.14)	(6.07)	(5.30)	(5.86)
County college count	6.697	3.637	3.078	4.591
	(8.462)	(3.579)	(3.748)	(6.174)
Observations (Colleges)	406	284	386	1,076

Note: Figures show averages across colleges. Standard deviations are placed in parentheses. Table 1 provides variable descriptions.

4 Results

Tables 3 and 4, respectively, show the average treatment effects of teaching modalities on COVID-19 cases and deaths. We begin with simple bivariate OLS to test the correlation, then control for other covariates, and then use three matching models. Apart from the bivariate OLS (Model 1), all control variables were used in all estimates (Models 2–5).

Table 3. Average Treatment Effects on COVID-19 Cases
(Dependent variable: % change in cases compared to cases in 2 weeks before reopening date.)

Model	Treatment	(1) 0–15 Days	(2) 15–30 Days	(3) 30–45 Days	(4) 45–60 Days
1. Biv. OLS	1. In-person = 1, online = 0	18.291**	22.265	38.044	24.598
		(9.259)	(13.625)	(24.626)	(29.549)
	2. In-person = 1, hybrid = 0	12.768	3.537	27.221	21.753
		(10.273)	(20.489)	(30.055)	(34.139)
	3. Hybrid = 1, online = 0	5.552	18.532	22.661	19.474
		(8.497)	(16.705)	(17.007)	(23.512)
2. Mult. OLS	1. In-person = 1, online = 0	33.152**	39.162*	60.235	
		(15.203)	(21.994)	(37.523)	4.856 (38.79)
	2. In-person = 1, hybrid = 0	23.629*	18.091	39.057	3.023
		(12.96)	(21.659)	(33.033)	(37.159)
	3. Hybrid = 1, online = 0	4.261	10.94	20.976	39.665
		(12.189)	(18.592)	(16.925)	(30.561)
3. PSM	1. In-person = 1, online = 0	35.052***	36.061*	49.915	21.246
		(13.174)	(19.77)	(33.179)	(33.564)
	2. In-person = 1, hybrid = 0	22.983*	17.79	41.661	15.955
		(13.02)	(22.032)	(33.546)	(39.944)
	3. Hybrid = 1, online = 0	6.607	3.782	18.706	26.166
		(10.74)	(16.098)	(19.398)	(44.361)
4. NN	1. In-person = 1, online = 0	24.459*	26.044*	46.144*	48.135*
		(12.881)	(14.811)	(25.293)	(27.656)
	2. In-person = 1, hybrid = 0	20.004**	18.501	41.576**	48.599*
		(9.765)	(14.026)	(20.643)	(28.815)
	3. Hybrid = 1, online = 0	7.311	11.901	10.299	15.661
		(11.304)	(18.141)	(13.583)	(21.643)
5. KMDM	1. In-person = 1, online = 0	35.014***	54.036***	79.443***	81.676**
		(10.631)	(15.375)	(28.319)	(36.443)
	2. In-person = 1, hybrid = 0	18.265	12.657	35.801	21.845
		(12.887)	(22.913)	(31.083)	(40.897)
	3. Hybrid = 1, online = 0	14.813	27.690	33.37**	53.353*
		(10.944)	(19.227)	(16.514)	(28.153)

Note: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. $N = 1{,}076$. Model 1 has no control variable. Models 2–5 have the same control variables. Control variables are listed in Table 5 and matching performance is reported in the appendix (Figure A1). State fixed effects were also used but not reported. Biv. = Bivariate, OLS = Ordinary Least Squares, Mult. = Multiple, PSM = Propensity Score Matching, NN = Nearest Neighbor, KMDM = Kernel Multivariate Distance Matching.

Table 3 suggests that the association of in-person teaching with COVID-19 cases, as opposed to online, is positive and significant. For example, the bivariate model shows that cases increase by 18.29 percentage points in the first 15 days after reopening compared to the 15 presemester days. However, all other treatments and later periods are not statistically significant in the bivariate model. The gap between the effects of in-person and online stays significant when we control for other covariates, using multiple OLS, PSM, NN, and KMDM, respectively, but becomes insignificant for multiple OLS and PSM as

Table 4. Average Treatment Effects on COVID-19 Deaths
(Dependent variable: % change in deaths compared to deaths in 2 weeks before reopening date.)

Model	Treatment	(1) 0–15 Days	(2) 15–30 Days	(3) 30–45 Days	(4) 45–60 Days
1. Biv. OLS	1. In-person = 1, online = 0	6.957	10.057	10.966	1.841
		(8.163)	(10.674)	(11.535)	(15.012)
	2. In-person = 1, hybrid = 0	14.127	22.991**	13.781	17.915
		(8.809)	(11.044)	(12.559)	(17.359)
	3. Hybrid = 1, online = 0	3.847	0.669	9.568	-1.631
		(7.045)	(9.995)	(10.358)	(13.33)
2. Mult. OLS	1. In-person=1, online = 0	13.789	23.266*	6.053	-15.816
		(11.488)	(13.931)	(14.993)	(22.799)
	2. In-person = 1, hybrid = 0	26.791**	23.111	12.67	22.044
		(11.299)	(15.512)	(14.917)	(21.657)
	3. Hybrid = 1, online = 0	-1.979	4.448	3.897	-17.015
		(9.098)	(12.649)	(13.085)	(16.629)
3. PSM	1. In-person = 1, online = 0	10.704	18.588	4.863	-2.444
		(10.877)	(14.882)	(16.026)	(26.242)
	2. In-person = 1, hybrid = 0	25.247**	9.418	-4.274	7.128
		(12.406)	(19.31)	(16.85)	(21.691)
	3. Hybrid = 1, online = 0	-1.216	-2.301	-1.16	-25.527
		(8.448)	(11.778)	(12.788)	(16.251)
4. NN	1. In-person = 1, online = 0	9.595	12.683	5.308	3.521
		(10.205)	(16.835)	(16.344)	(20.662)
	2. In-person = 1, hybrid = 0	11.968	8.134	12.879	41.827**
		(10.81)	(15.865)	(15.744)	(21.125)
	3. Hybrid = 1, online = 0	-10.882	-4.681	-6.098	-19.883
		(7.777)	(9.122)	(11.438)	(14.994)
5. KMDM	1. In-person = 1, online = 0	20.185**	29.215**	39.461***	38.404*
		(8.953)	(11.474)	(12.565)	(19.662)
	2. In-person = 1, hybrid = 0	24.329**	26.296*	24.879*	31.853
		(10.325)	(13.466)	(14.868)	(20.131)
	3. Hybrid = 1, online = 0	0.727	4.734	15.209	5.31
		(7.38)	(9.833)	(10.742)	(14.044)

Note: Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. $N = 1{,}076$. Model 1 has no control variable. Models 2–5 have the same control variables. Control variables are listed in Table 5, and matching performance is reported in the appendix (Figure A1). State fixed effects were also used but not reported. Biv. = Bivariate, OLS = Ordinary Least Squares, Mult. = Multiple, PSM = Propensity Score Matching, NN = Nearest Neighbor, KMDM = Kernel Multivariate Distance Matching.

we move beyond 30 days. A significant effect in later periods is important from a policy perspective because the difference in cases in the first 15 days can be influenced by mandated testing for in-person teaching mode. Matching with propensity scores does not offer a significant advantage over multiple OLS regression. Matching with NN somewhat corroborates the result and indicates an increase of 48 percentage points in 2 months after reopening. The gap between in-person and hybrid is similar (48 percentage points) by the first 2 months of reopening, as indicated by the NN model (Table 3).

However, PSM collapses all data dimensions into one, whereas NN is vulnerable to the availability of closest neighbors on all dimensions. A more appropriate and robust method for our analysis is KMDM because it separately performs matching on each dimension. Estimates from NN in Table 3 suggest a statistical difference in COVID-19 cases between in-person and online groups for all periods. For instance, a college reopened with an in-person teaching mode may have 54 percentage points more cases in the county than the preopening 15 days in the first month, compared to a similar college with an online teaching mode. The figure becomes 81 percentage points after the first 2 months.

Interestingly, KMDM results show that the hybrid teaching mode has a positive significant difference from online in later periods. Although the gap between hybrid and online is insignificant in the first month, colleges with hybrid modes have an increase of 53 percentage points in cases as opposed to colleges with online modes by the end of the second month. The gap between in-person and hybrid remains statistically insignificant. That is, the hybrid mode follows the pattern of in-person after 30 days. To summarize, colleges that chose in-person are associated with a greater increase in COVID-19 cases in their respective counties, compared to the colleges that chose online. A hybrid instructional mode may create a difference from in-person at the beginning, but may not sustain for longer periods, possibly because the spread from in-person components overwhelms the gain from online components due to the exponential nature of the disease spread.

Table 4 presents estimation results for COVID-19 deaths. Relatively simpler models (1–3) show some positive significant differences between in-person and hybrid within the first month. It is possible that colleges with high presemester cases influenced the death rates within 30 days when control variables were not properly matched. However, as a more robust method, KMDM captures a statistically significant difference between in-person and online modes, which grows over time at a decreasing rate. For example, teaching in-person as opposed to online is associated with 29 percentage points more deaths in the first 30 days after reopening compared to the 15 presemester days, and 38 percentage points more deaths in the first 60 days after reopening. Similar to the results we found for COVID-19 cases, hybrid modes create a statistically significant difference in death rates from in-person for the first 45 days, but the difference gradually dissolves beyond that period.

In short, the magnitude of the average treatment effects increases at a decreasing rate as we go from 0–15 days to 45–60 days in both Tables 3 and 4. This occurs because college reopening increases average cases and deaths regardless of teaching modality. Although online mode raises the rates slower than in-person, the gap starts to shrink after 45 days, possibly because college students are likely to socialize on campus outside the classroom even if the classes are online.

The data set further allows us to explore another aspect of teaching modality during a pandemic. We use logistic regressions to find the predictors of a teaching modality. The results in Table 5 show that colleges with greater enrollment are less likely to choose in-person than online (column 1), and in-person than hybrid (column 3), holding other variables constant. A percent increase in endowment per student decreases the log odds ratio of choosing in-person over online by 0.616, and that of choosing hybrid over online by 0.476, given the other predictors. More population in the county might have made colleges choose remote teaching components. For example, colleges in counties with a percent more population are associated with 0.812 lower log odds of choosing in-person modes over online. The negative association of in-person mode with enrollment and population variable implies that the colleges might have considered remote teaching elements where campuses are more likely to be crowded.

Table 5. Predictors of Teaching Modalities (Logistic Regression Coefficients)

Variables	(1) In-person = 1, online = 0	(2) Hybrid = 1, online = 0	(3) In-person = 1, hybrid = 0
% stayed home	-0.0289	-0.00890	0.0122
	(0.0514)	(0.0536)	(0.0380)
Log enrollment	-0.616***	-0.177	-0.476***
	(0.192)	(0.192)	(0.160)
Log cost of attendance	0.568	0.378	0.400
	(0.711)	(0.756)	(0.696)
Log endowment per student	-0.436***	-0.388***	-0.108
	(0.152)	(0.147)	(0.103)
Log student-faculty ratio	-0.820*	-1.125**	0.393
	(0.444)	(0.465)	(0.385)
Public = 1, 0 otherwise	-0.895	-1.044	0.0880
	(0.666)	(0.703)	(0.625)
Log total population	-0.812***	-0.392	-0.155
	(0.289)	(0.287)	(0.239)
Black population (%)	0.00524	0.00325	0.0184
	(0.0203)	(0.0204)	(0.0170)
Male population (%)	-0.103	-0.0116	-0.0679
	(0.103)	(0.116)	(0.0870)
Log household income	1.338*	1.018	0.133
	(0.753)	(0.771)	(0.661)
Republican votes (%)	0.0462***	0.0156	0.0346**
	(0.0177)	(0.0178)	(0.0154)
Mask ordinance = 1, 0 otherwise	1.731	-1.075	-0.141
	(1.126)	(1.337)	(1.254)
Rural campus = 1, 0 otherwise	-0.761	-0.278	-0.186
	(0.478)	(0.516)	(0.372)
Log cases in spring 2020	0.334	0.224	0.00667
	(0.287)	(0.272)	(0.190)
Log deaths in spring 2020	-0.0715	-0.0367	-0.121
	(0.233)	(0.216)	(0.164)
Temperature in reopening month	0.0108	-0.0684	0.0940
	(0.0562)	(0.0557)	(0.0575)
County college count	0.0213	-0.0218	0.0430
	(0.0618)	(0.0356)	(0.0536)
Constant	1.868	1.836	-6.738
	(11.64)	(14.27)	(10.78)
Observations (colleges)	406 + 386 = 792	284 + 406 = 690	386 + 284 = 670
Accuracy	78.50%	70.45%	69.19%
Wald χ^2	149.68***	75.28**	78.33**
Log pseudolikelihood	-224.37	-243.49	-299.97
Pseudo R-squared	0.334	0.168	0.152

Note: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. N = 1,076. The third category is omitted from the sample for each pairwise comparison. For example, 406 online + 386 in-person colleges make 792 colleges in column (1), 284 hybrid and 406 online make 690 colleges in column (2), and so on. State fixed effects were added but not reported. We use log forms of some predictors to reduce the influence of extreme values on coefficient estimates. Accuracy shows the percentage of teaching modalities correctly identified by the model. The pseudo R-squared is higher (0.33) for the in-person versus online prediction (column 1) as opposed to hybrid versus online or in-person versus hybrid. This occurs because hybrid teaching modes are widely heterogeneous across colleges and harder to measure and categorize. Nevertheless, the main interest of this study is to analyze the difference between full in-person and full online, which also gives us directions on their mixture (i.e., hybrid modes). Moreover, pseudo R-squared cannot be interpreted as the goodness of fit because, unlike the R-squared from OLS, it shows the improvement in model likelihood over a null model (e.g., Heinzl, Waldhor, and Mittlbock 2005; Hu, Shao, and Palta 2006; Hemmert et al. 2018). Table 5 also presents the accuracy of the logistic models, suggesting that the teaching modalities of about seven to eight colleges out of ten colleges were accurately predicted by our model.

Colleges with bigger class sizes, measured by the student-faculty ratio, were less likely to choose in-person teaching modes. The log odds ratio of choosing an in-person mode over online decreases by 0.82 as the student-faculty ratio increases by one percent, whereas that of hybrid decreases by 1.125 over online for the same increase in student-faculty ratio. Table 5 also shows that greater Republican votes in the 2016 election have a positive association with choosing in-person mode over online or hybrid. As discussed in the data section, political views in a county might have played a role in the selection of teaching modality. Interestingly, the real household income in the county has a positive relationship with in-person teaching mode as compared to online. Since college-level financial variables are already controlled for, a possible explanation for this is that wealthier counties preferred in-person over online to reduce the stress and to ensure the quality of education (e.g., Kofoed et al. 2021; Lazarevic and Bentz 2021; Orlov et al. 2021).

The above results are based on the full model that was constructed based on the literature. Some control variables can be correlated, which reduces the precision of estimated coefficients in the logistic model. Figure A2 in the appendix presents the correlation heat map of control variables. Not surprisingly, total population and COVID-19 cases and deaths in the spring semester are highly correlated (0.90). Since total population is a critical predictor of disease spread, and it also appeared significant in the selection of teaching modes (Table 5), we kept total population in the model and dropped spring cases and deaths variables, and repeated the above analysis for robustness. The results are presented in the appendix Tables A1–A3. Treatment effect estimates in Table A1 and A2 are almost the same and corroborate our previous observations from the KMDM model. The noticeable difference in the logistic model results (Table A3) is that rural campus variable becomes statistically significant; that is, colleges in rural areas are less likely to choose in-person over online. This can be attributed to the colleges in urban areas that decided to reopen with online modes due to high COVID-19 cases or deaths in the spring semester. Thus, dropping spring outcomes made the rural versus urban variable significant.

5 Concluding Remarks and Implications

What do these results imply? Assume two similar counties with two comparable colleges, and each county reported 100 COVID-19 cases before fall 2020 semester. Further assume that the first county has its college reopened online, and has 10 more COVID-19 cases in 2 months. If the college in the second county reopened in-person, then its county may have 18 more cases in 2 months, ceteris paribus. Again, assume 100 COVID-19-related deaths before fall 2020 semester in each of these two counties. If the first county observes 3 deaths in 2 months, the latter county observes 4 deaths. Moreover, if the second college reopens with a hybrid mode, then the number of cases and deaths, respectively, would be 15 and 4 in 2 months because hybrid modes make a difference from in-person only at the beginning, but reaches up to the level of in-person within 2 months.

We found a statistically significant association between teaching modalities and COVID-19 outcomes, which is consistent with several studies that find a negative impact of remote teaching or school closures on COVID-19 outcomes (e.g., Andersen et al. 2020; Auger et al. 2020; Pan et al. 2020; Chernozhukov et al. 2021), but our result contradicts the studies that find little or no negative impact (e.g., United Nations Children's Fund 2020; Herby et al. 2022). However, these studies analyze teaching modalities or closures of schools, and not colleges where students are more likely to be affected due to their age and the frequency of socialization (e.g., Wrighton and Lawrence 2020; Goodman et al. 2021). The only exception is Andersen et al. (2020) who analyzed college reopenings. Their preliminary findings suggest that college reopenings increase COVID-19 cases by 1.7 daily cases per 100,000 residents in the first 2 weeks. Assuming there was no case presemester, the exponential growth of 1.7 cases per day for 60 days generates a large number. However, we control for many college and county-level factors that Andersen et al. (2020) did not include in their (preliminary) analysis, which might have contributed to the difference.

Our findings have several implications for higher education and health policy that simultaneously apply to agricultural economics and agribusiness departments and/or land-grant universities. First, results from logistic regression suggest that colleges with bigger class sizes, having more populated campuses, or located in more populated areas chose remote teaching components (i.e., preferred online or hybrid to in-person modes). Although the rural campus variable is not a significant predictor in our results, many land-grant universities with urban or semi-urban campuses fall under this category. On the contrary, colleges with smaller endowments per student are less likely to choose online over in-person teaching modes, and hybrid over online modes, after controlling for other factors. Thus, relatively weaker positioned with heavy dependence on traditional on-campus tuition and auxiliary revenues would likely tend to return to the classroom with a quicker frequency out of financial exigency. Moreover, the average treatment effects show adopting an in-person mode instead of an online mode is associated with more COVID-19 cases. Therefore, colleges with small endowments need special policy attention to combat a disease-induced crisis.

Second, our results indicate that wealthier communities are more likely to have in-person teaching modalities, i.e., low-income communities are more likely to have remote teaching options given the resources available to their colleges. However, many studies discuss the added stress and the lack of social interactions in online instruction modes and hence poor student performance (e.g., Lazarevic and Bentz 2021; Kofoed et al. 2021; Orlov et al. 2021; Picault 2021). Thus, communities with low real income are in greater need of teaching resources on making online courses more interactive and performance-oriented.

Third, the analysis also suggests that campus reopening has a positive relationship with COVID-19 cases across all teaching modes, and both new cases and new deaths tend to increase for colleges teaching in-person compared to colleges teaching online. Since the treatment effects ideally find counterfactuals, one can point out that the expected risk of spreading a communicable disease can be partially mitigated with an initiative from the colleges by increasing distance education elements in classes. For hybrid modes, it is important to follow the containment policies at both the college and community level because we found that the in-person components of hybrid modes may influence the disease spread and undermine the expected benefits from remote instruction.

Our study is observational and not based on a randomized placebo-controlled trial, hence should be interpreted with great caution. However, it still finds significant patterns in the data, offering important insights about choosing a teaching modality during a disease-induced pandemic, given the college- and county-level features. Future research can look into the short-run and long-run effects of different teaching modalities on student learning outcomes.

About the Authors: Syed Badruddoza is an Assistant Professor at Texas Tech University (Corresponding author: syed.badruddoza@ttu.edu). Modhurima Dey Amin is an Assistant Professor at Texas Tech University.

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Case Study

Milner Ranch: Is the Grass Greener in Processing?

Hwangwon Lee[a], Tanner McCarty[a], Anastasia Thayer[b], and Ryan Larsen[a]
[a]*Utah State University and* [b]*Clemson University*

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Abstract
This case study explores the decisions facing a cattle producer in southern Idaho. Milner Ranch is a diversified family-run business that currently has cow-calf, grazing, and feedlot operations that produce 1,000 head of cattle per year for processing. Like other beef producers, Milner Ranch has recently faced bottlenecks in beef processing and an increasing gap between beef and fed-cattle prices. They wonder whether they would be better served by constructing their own beef processing plant rather than continue to deal with their regional processors. This case study pushes students to conceptualize and analyze the key economic tradeoffs (revenue, cost, risk, etc.) that come with expanding an agricultural firm's boundary. It also provides practice with examining the strengths and weaknesses of various transactional arrangements between producers and processors (marketing contracts, co-ops, and vertical integration).

1 Introduction

Milner Ranch sits at the base of the Albion Mountains. The region's rugged landscape and distance from major urban centers make it ideal cattle country. That is what brought Jack Smith here twenty years ago when he agreed to become the manager of Milner Ranch. Milner Ranch began with fifty head of black angus cattle and has since grown to over 1,000 head. Milner Ranch grazes their cattle on a combination of federal, state, and privately owned grazing leases. They have worked with their local conservation district to increase water storage and irrigation capacity on their operation. Milner Ranch provides all the feed their livestock need either through their grazing lands or the hay/grass that they harvest each year. This ability to feed their cattle inexpensively has provided them with growth opportunities. At each growth opportunity, Milner Ranch has looked for ways to increase efficiency and profitability. Milner Ranch focused purely on selling calves in the beginning. Identifying potential opportunities, they expanded operations and acquired a feedlot. The addition of the feedlot has enabled Milner Ranch to control cattle production from calf to finishing. The ability to provide low-cost feed and produce high quality animals has helped Milner Ranch manage the risk that is inherent within the cattle industry.

Recently, Jack listened to the *Wall Street Journal Podcast* (2022), which got him thinking about expanding his business into meat processing. Like many ranchers, Jack has always had a complicated relationship with local beef processors. Processors provide a valuable service, but it always feels like processors end up with the lion's share of the beef-marketing profits. Jack has also been reading about the supply chain issues in the beef processing industry that were highlighted during the COVID-19 pandemic (Cowley 2021). Jack has considered that perhaps some smaller scale processing facilities could mitigate some of the supply chain issues present in the beef processing industry.

Milner Ranch adheres to specialized production practices for their cattle. Their cow-calf, grazing, and finishing operations are both Global Animal Partnership (GAP) 2 certified (USDA 2022a). This means that they do not use any antibiotics, growth hormones, or feed containing animal by-products. They also open their practices to independent auditors every fifteen months to maintain this status. Milner Ranch also maintains a Certified Angus Beef (CAB) designation for its cattle. This requires cattle to be at least 51 percent black hided (a dominant genetic trait within Angus cattle) or have verified Black Angus genetics. The CAB designation also requires that the beef grade as either prime or the top two categories of choice

at processing. Milner Ranch gets this rating for 80 percent of their cattle, but it requires special attention to genetics and feeding practices.[1] Owning a processing plant may allow Milner Ranch more control over marketing their specialty beef and allow for a higher margin on their cattle than they currently receive from processors.

On the other hand, beef processing plants are an expensive and a somewhat irreversible investment. Even a small plant capable of processing 1,000 head of cattle per year would cost around $1.9 million just to get the plant up and running. An unprofitable processing plant would reduce Milner Ranch's available liquidity and could starve their successful feedlot and grazing operations of financial capital. The owners of Milner Ranch share Jack's interest in a potential processing plant. They are so interested that they have a meeting scheduled for tomorrow to discuss the viability of this processing plant. Before the meeting, Jack has three primary questions to answer: Should Milner Ranch build and operate a beef processing plant? If they build a plant, how large should it be? If they build a plant, how should they acquire sufficient cattle to run it at capacity? Jack has a lot to consider before his meeting.

1.1 Learning Objectives of This Case Study

1. *Should Milner Ranch build and operate a beef processing plant?* Students should gain insight into the tradeoffs associated with expanding the boundaries of a beef livestock producer into processing in terms of revenue, costs, and risk exposure in a dynamic context.
2. *If they build a plant, how large should it be?* Students should learn to define and conceptualize the tradeoffs associated with various processing plant sizes, and how these tradeoffs affect margins at a beef processing plant.
3. *If they build a plant, how should they acquire sufficient cattle to run it at capacity?* Students should learn the tradeoffs associated with increased processor and producer coordination.

2 Cattle Industry Overview

The United States is a global leader in cattle production, characterized by the largest fed-cattle industry in the world (USDA 2021b). Further, the cattle-beef supply chain is an important agricultural sector within the United States. In 2020 the cattle/calves sector represented the largest sector of all livestock or crops produced in the United States by cash receipts (Economic Research Service 2022a). In 2020 the retail value of all beef produced was estimated to be $123.3 billion (Economic Research Service 2022b). The cattle supply chain is uniquely characterized by geographically dispersed stages of production and cyclical expansions and contractions in the national herd size (Drouillard 2018).

Cattle begin their life cycle on cow-calf operations and then get sent to grazing/range operations. These first two stages are spread across the United States. Once they have grown to a sufficient weight grazing, usually somewhere between 600 and 800 pounds, cattle are relocated to feedlot operations typically located in the middle of the country (Figure 1). As a result of geographically distinct areas for cow-calf grazing operations and feedlots, the cattle supply chain is dependent on long-haul trucking routes for individual cattle. In 2003, approximately 57 percent of cattle born in the United States were shipped interstate, which doesn't include intrastate shipments that are present in states with feedlots, such as Colorado, Kansas, Nebraska, and Texas (Shields and Mathews 2003).

Compared to their counterparts in southern and southeastern states, cattle operations in the Intermountain West are characterized as grazing operations. Surveys of producers in the west suggest that nearly all operations have cows in their herd, and approximately half are exclusively cow-calf operations (Asem-Hiablie et al. 2017). Some finishing occurs on farm, with approximately 15 percent of operations finishing on the ranch in northwestern states (Idaho, Montana, Oregon, Washington, and

[1] Beef is graded by U.S. Department of Agriculture (USDA) meat inspectors. Grading for quality comes down to meat marbling, which affects tenderness, juiciness, and flavor of the beef. The highest possible USDA beef grade is prime, followed by choice, followed by select (USDA 2019). Higher grades fetch higher selling prices.

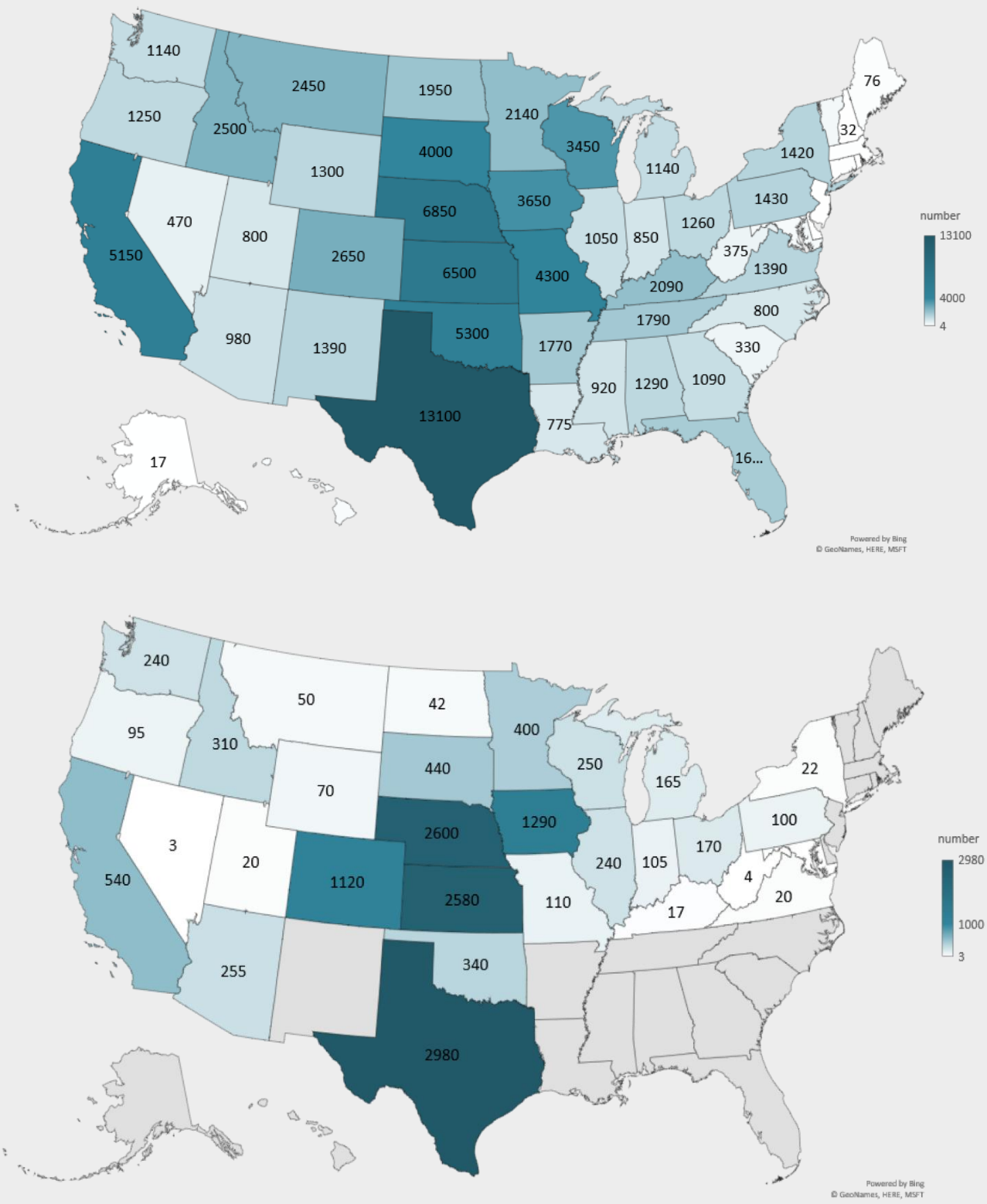


Figure 1. Total Cattle (thousands), January 1, 2021 (top) and Cattle on Feed (thousands), January 1, 2021 (bottom).

Source: National Agricultural Statistics Service 2021.

Wyoming) and 22 percent finishing in southwest states (Arizona, California, Colorado, Nevada, New Mexico, and Utah).

In addition to variation in local production practices and farm size, it is important to understand that total cattle inventories in the United States have declined since the late twentieth century (Figure 2). Further, the cyclical nature of the roughly ten-year cattle cycle leads to fluctuations in inventory over the cycle, which drives national prices and herd size. The negative relationship between prices and inventory can be an important driver for on-farm management decisions.

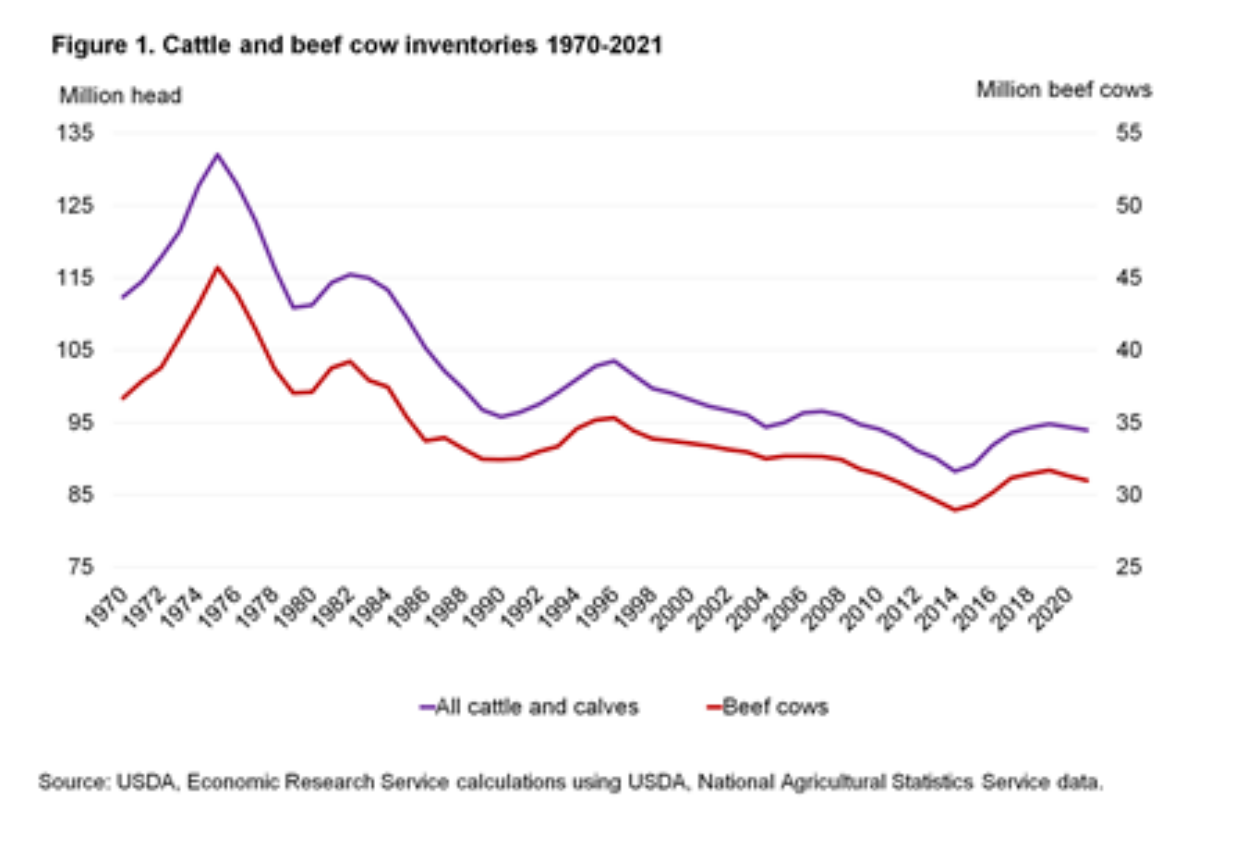
Finally, vulnerabilities exist in the current supply chain that highlight the need for additional processing capacity. There is growing concern that the segregated production stages of the cattle and beef industry, consolidation in the packing and processing, and reliance on transportation, renders the industry vulnerable to supply chain disruptions. This vulnerability was highlighted on two recent occasions: when a fire broke out in a Tyson beef processing plant in Holcomb, Kansas (Dennis 2020), and when the COVID-19 pandemic led to widespread packing plant closures (Hirtzer and Freitas 2020). Individually, each incident caused enough market disruption (rising beef prices and falling live animal prices) that the President asked the U.S. Department of Justice to look into allegations that U.S. meat packers broke antitrust law.

While most recent events have been linked to processing capacity, other vulnerabilities exist in the feedlot sector and for small cow-calf producers, specifically, industry reliance on long-haul trucking routes. Shortages in trucks, drivers, changes to transportation routes, transportation policies, and fuel costs could all have a negative and significant impact on the cattle supply chain. For this reason, developing regional processing capacity that would eliminate some of the beef industry's reliance on trucking would increase resilience of the supply chain.

2.1 Domestic and International Beef Demand

Total cattle inventory declines in recent decades have mirrored the fall in domestic demand for beef. While per capita beef consumption has decreased since the late 1990s (Figure 3), spending has remained relatively constant at 2–2.5 percent of disposable household incomes spent on beef (USDA 2021a). There still remain concerns about the long-term demand for beef and shifting consumer preferences to poultry or meat alternatives (Davis and Lin 2005; Bryant 2019).

While there have been decreases in per capita domestic beef demand, international beef exports have grown over the same time period. The value of exports decreased slightly in 2020 due to the pandemic, but the average value of beef exports from 2016 to 2020 was $7.55 billion (USDA 2021b). Over the last five years, the top countries importing U.S. beef included Japan (valued at $1.88 billion), South Korea (valued at $1.52 billion), Mexico (valued at $995 million), Canada (valued at $735 million), and Hong Kong (valued at $789 million).



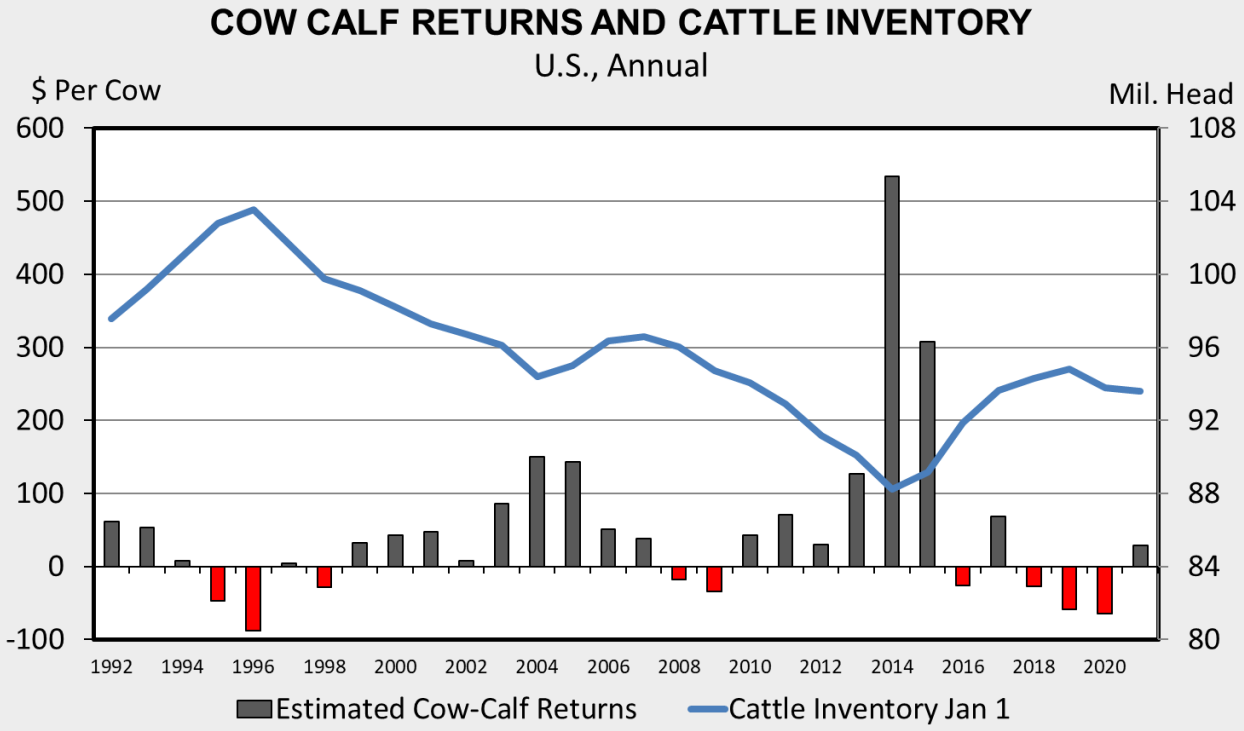


Figure 2. Total Cattle Inventories 1970-2021 (left) and Corresponding Prices (right)

Source: Economic Research Service 2022a.

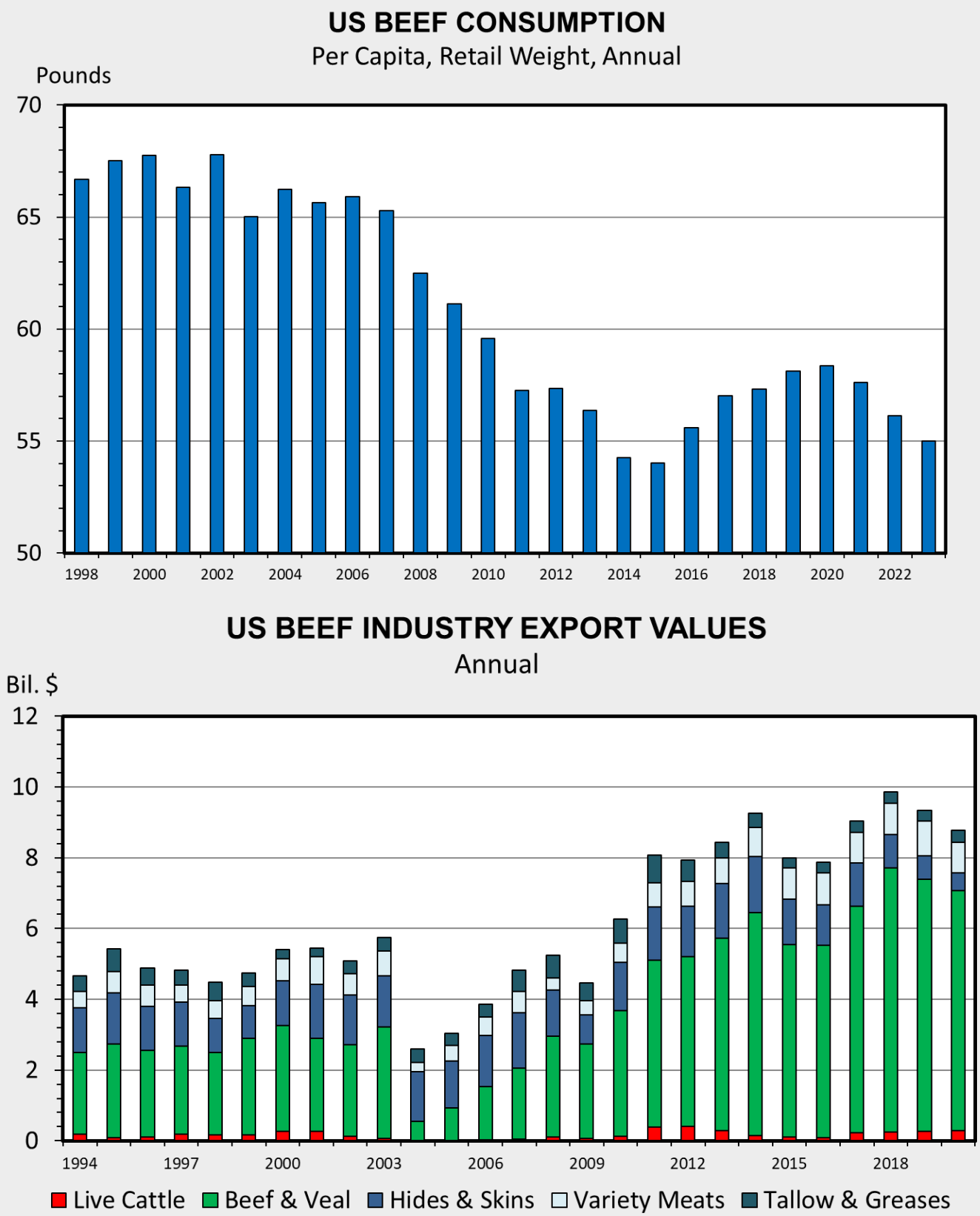


Figure 3. U.S. Beef Consumption (left) and U.S. Beef Industry Export Values (right)

Source: USDA 2022b.

2.2 Future Issues

The cattle and beef industry appear to be in a period of transition. Pressure to reduce climate impacts, new international consumers, and competition from plant-based protein sources appear to be the greatest threats, as well as potential opportunities for the beef industry to meet changing preferences of consumers.

2.2.1 Climate Change and Emissions

The cattle industry has come under scrutiny and criticism for greenhouse gas emissions, reactive N emissions, deforestation, land use change, and runoff (Gerber et al. 2013; Rotz et al. 2019). Globally, the livestock industry is responsible for 14.5 percent of greenhouse gas emissions, which has caught the attention of the general public, putting greater scrutiny on the cattle industry and increasing pressure for the industry to address the effects of climate change (Carroll 2019; Kaplan 2019; Quinton 2019). In response, growing consumer consciousness and increasing preferences for reducing the environmental impact of food choices are new areas for both research and producers to capture additional market share (Lusk and McCluskey 2018).

The industry has sought to quell these concerns by making commitments for increased transparency and sustainable sourcing.[2] In particular, large retailers such as Walmart and McDonald's have sustainability plans to convince consumers of their commitment to a more environmentally friendly supply chain (McDonalds 2019; Walmart 2020). On the production side, large processors such as Cargill and JBS are now publicizing their environmental impacts with commitments to improvement in the areas of water use, emissions, and energy use (JBS 2020; Cargill 2022). In the most ambitious commitment yet, the National Cattlemen's Beef Association in August 2021 announced that the industry would achieve carbon neutrality for U.S. cattle production by 2040 (Stewart 2021).

While the cattle and livestock industry has faced increasing pressure from consumers to change production practices, how these plans manifest in practice, and their subsequent impact on the industry remains to be seen.

2.2.2 International Markets

Looking forward, there is a lot for beef processors to be excited about. World population growth combined with income growth continues to expand opportunities for beef processors. China in particular has recently become a major consumer of U.S. beef. This trend is displayed in Figure 4. While international beef trade is highly dependent on trade agreements, cattle exports to China reached nearly 50 million pounds in April 2021. Further, Chinese imports have increased 210 percent from 2019 to 2020 (USDA 2021b). While the value of trade is only $310 million in 2020, the opportunities for export of beef and growing demand from other countries remains to open future marketing opportunities for domestic producers.

2.2.3 Plant-Based Alternatives

There are also a fair amount of future headwinds for producers to be wary of. For decades, traditional beef substitutes such as chicken and pork have threatened the industry. Now, they will also have to face growing competition from nontraditional sources such as lab-grown and plant-based meat (PBM). A survey by Bryant (2019) illustrates consumer familiarity and acceptance of lab-based meat and PBM in the United States, with 29.8 percent of respondents indicating they would be extremely or very likely to purchase lab-based meat, and 32.9 percent of respondents were either very or extremely likely to purchase PBM alternatives. Researchers Hoek et al. (2013) found that sampling vegetable-based or clean

[2] Sustainable sourcing is a broad category but typically refers to the inclusion of environmental and social criteria in supply chain decisions. This can take the form of reductions in energy, water, or chemical footprints in agricultural production. It can also take the form of animal or worker welfare considerations.

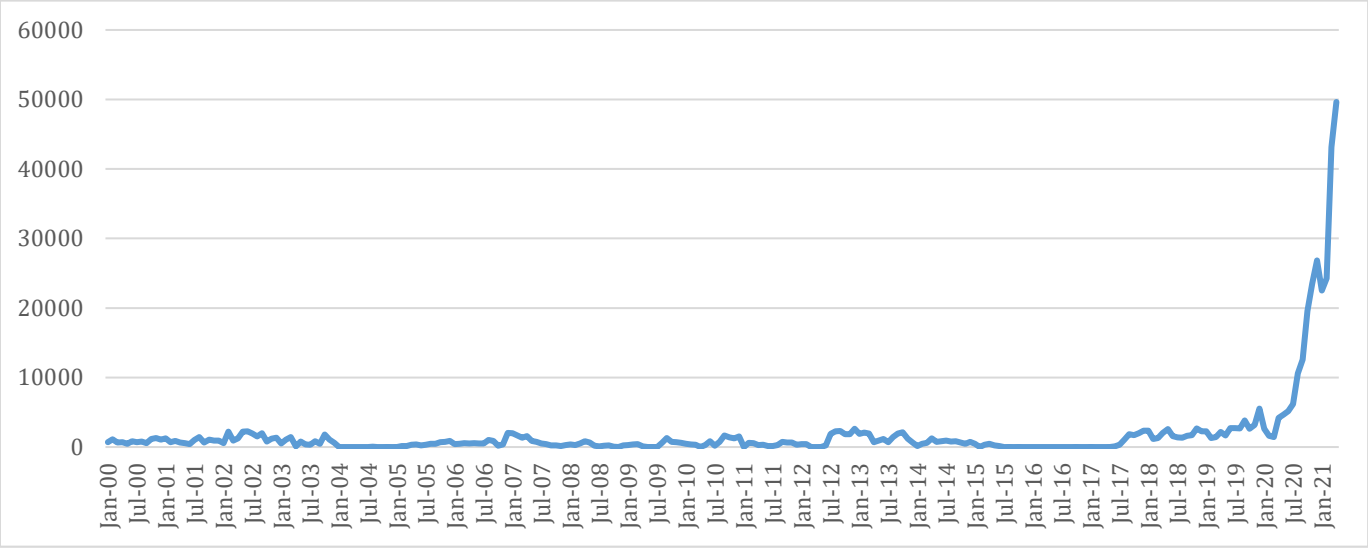


Figure 4. U.S. Beef Export to China (January 2000-April 2021)

Source: USDA 2021b.

meat reduces consumer aversion to it. Thus, people can become used to consuming beef substitutes. PBM or lab-grown meat, also called cell-based meat (CBM), has the potential to alleviate climate-related, environmental, health, or animal welfare issues associated with traditional beef production practices.

On the other hand, PBM and CBM substitutes have their limitations. Most Americans have a robust preference for eating natural beef rather than choosing PBM or CBM. In one research result, Van Loo et al. (2020) show that 72 percent of respondents they surveyed preferred to purchase farmed beef. Furthermore, market preference for farmed beef soared to 80 percent when specific brand names, such as Certified Angus Beef, Beyond Meat, Impossible Food, and Memphis Meats were explored. Hence, the movement to alternative beef exists, but the preference for genuine beef remains significant.

2.3 Beef Industry in Southern Idaho

While most people think of Idaho when they think about potatoes, cattle represents an even larger sector within the state. In 2019, cattle and calves was the second most valuable commodity at $1.4 billion, while potatoes came in third at $1.1 billion (National Agricultural Statistics Service 2021). Southern Idaho's extensive public grazing land makes it desirable for cattle production. Grazing allotments are relatively cheap and easy to obtain. Over 70 percent of the state is composed of public land. Grain for running a feedlot is a little more expensive than in the Midwest, but with the nearby city of Burley sitting right on a freight train line and Interstate 84, the basis for feedlot grain remains modest.

The labor pool in the Burley area is fairly shallow. Burley sits at the intersection of Cassia and Minidoka Counties, which have a combined population of about 45,000 people. Given Idaho's 3.2 percent unemployment rate, plant workers and skilled supervisors may be tough to find. Jack's rough estimate suggests Milner Ranch would require somewhere between five and seventy-five additional workers depending on the size of the beef processing facility. Jack thinks that they could get the workers they need in either case but may have to pay a premium if they need a large number of employees.

Another consideration for Jack is that Milner Ranch would not be the only beef processing plant in the region. JBS has a 500,000 head per year processing plant 140 miles to the Southeast in Hyrum, Utah. Caviness and Simplot (CS) jointly run a 442,000 head per year processing plant 166 miles to the northwest in Kuna, Idaho. Two new facilities are being built within just a couple hours of Milner Ranch.

True West Beef is being built just to the west of Burley, and Intermountain Packing is building a facility in Idaho Falls. Both of these facilities should be operational within one year. USDA surveys from 2017 estimate that Idaho and its surrounding states (Montana, Nevada, Oregon, Washington, Wyoming, and Utah) produce a combined total of about 449,000 fed cattle annually (National Agricultural Statistics Service 2021). This means that there is currently a surplus in regional processing capacity for fed cattle. While it is not required to source cattle from within the region, it would add to Milner Ranch's transportation cost if they had to acquire fed cattle from outside the region.

3 History of the Business

3.1 Mission Statement

Milner Ranch has always prided itself on producing the highest quality beef possible. Eighty percent of its fed cattle grades at prime or upper tiers of choice, helping to achieve its CAB certification. The majority of what doesn't make CAB grade still receives choice grade. While consolidation swept across various grazing and feedlot operations to achieve economies of scale, Milner Ranch bucked this trend. In response, they doubled down on improving genetics and management practices to improve the quality of their beef (e.g., CAB certifications). They have also experienced success by following production practices aimed at achieving animal welfare accolades (e.g., GAP 2 certification). Both of these support Milner Ranch's mission of producing the best beef possible, while allowing them to earn a premium on their product in the market.

Their decision to not follow the conventional wisdom in U.S. agriculture of "get big or get out" is by choice rather than lack of financing. Their cow-calf, grazing, and feedlot operations have been successful, and they have the resources to aggressively expand any and/or all of these operations. However, they feel too much expansion in any area would make it difficult to maintain their self-imposed high standards. Their hope is that a successful processing plant would complement their core philosophy of doing everything they can to produce the best beef possible for the consumer by giving them more control over the marketing process.

3.2 Grazing Operation

Milner Ranch has been in ranching for multiple generations. When Jack took over management of the operation more than two decades ago, he made it a priority to cut costs and make the operation profitable. The grazing operation follows a traditional cow-calf operation in Idaho with spring calving, maintaining a herd of approximately 1,200 cows and 48 bulls. During this time, the herd is on hay and straw moving to a private pasture through the spring melt. The herd moves to public grazing lands during the summer months, returning to private pasture and range land during the fall. In terms of the operation, Jack has worked to enforce and maintain a 12 percent cow replacement rate, a 2 percent cow death loss, and 88 percent calf weaning rate. These efforts have helped maintain the health of the herd. For the purposes of sale, Jack assumes calves wean at eight months and weigh approximately 510 pounds for heifer calves and 550 pounds for steer calves.

3.3 Feedlot Operation

For the last ten years, Milner Ranch has operated a feedlot. Jack operates the feedlot as a separate operation from the cow-calf herd. This has helped track profitability across the two operations. The weaned calves move into the feedlot in late fall and begin on a starter ration for sixty days before moving to a finish ration for 200 days. Given that calves are moving from the cow-calf operation without additional purchased cattle, it is assumed that approximately 70 percent of the calves are steers and 30 percent are heifers. The steers are assumed to have 2.7-pound average daily gain (ADG) over the starter rations and 3.5-pound ADG when feeding finish rations, being fed to a weight of 1,350 pounds. Heifer

calves are assumed to finish at 1,275 pounds. Feed rations are generally a mixture of alfalfa hay, corn silage, grains, minerals, and salts. Given that the land is generally poor for crop production, the operation is forced to purchase their silage and grains. They grow their own hay. Finally, unlike other operations that cycle cattle, this feedlot assumes one cycle of 1,000 head of cattle.

4 Beef Processing Plant Decision Considerations

Milner Ranch will ultimately make a decision based upon Jack's recommendation. Jack has identified three key questions and two key variables that will dictate whether a processing plant makes sense. These questions include: should Milner ranch invest in a processing plant, if they invest in a processing plant how large should it be, and how should they maintain relationships with feedlots?

4.1 How Large Should a Potential Processing Plant Be?

Jack doesn't think that the region Milner Ranch operates in would benefit from constructing a large-scale processing plant (over 100,000 head per year). There are already two such plants in the region, and Milner Ranch does not have the liquidity or the appetite for risk to make that large a plant interesting to them or profitable. He has narrowed the size decision down to either a 1,000 head per year processing plant (small-scale) or a 20,000 head per year plant (mid-scale). Either of these sizes comes with its own benefits and costs.

4.1.1 Small-Scale Plant

The major benefit of a small-scale plant is that Milner Ranch could feed this plant entirely with its own cattle. This would give Milner Ranch total control over the cattle within its operation from birth to processing. This control could lead to the ability of marketing their beef as high-end and fully capturing the benefits and higher price premium associated with how they already raise their cattle. Milner Ranch also wouldn't have to worry about regional competition from larger processors for fed cattle since they would be able to run this plant at capacity with their own herd. Finally, a small plant requires considerably less up-front costs than larger scale plants. After some preliminary research, his ballpark estimate for the cost of constructing a 1,000 head per year plant is $1.9 million. Milner Ranch has $4 million in financial capital, so they could pay for this in cash if they desired to do so.

The main drawback of a small beef processing plant is the operating cost and its effect on long run average total cost. This plant would lack the economies of scale that larger regional competitors have. Jack's rough estimated long run average total cost of processing cattle into beef is about $5.50 per pound of meat produced for a small plant. Last Jack checked, average weighted prices for various beef cuts were wholesaling for about $5.10 per pound in the area.[3] This means that even with beef prices on the rise, Milner Ranch would still need to achieve premium above-market wholesale beef prices to cover the costs of being small. Another consideration is that the size of the plant puts a lot of pressure on the grazing and feedlot divisions of the operation. High death loss in either stage of production will leave the processing plant with idle capital, which would quickly increase the long run average total cost of production. While Jack has a lot of faith in these other divisions, he is the one running them after all; it leaves little room for error or unexpected events.

4.1.2 Mid-Scale Plant

The mid-scale plant provides a compromise between the economies of scale of a large plant and the increased quality control and marketing that a small plant provides. A 20,000 head per year processing plant has a lower long run average total cost of production compared to the small-scale plant, estimated at $5.00 per pound of meat produced. This would make the plant profitable under current prices. Milner

[3] One fed steer produces multiple cuts of meat. Each cut has a different price. We weight the different prices associated with different cuts as well as their percent occurrence. On average, processed beef is worth $5.10 per pound.

Ranch would have to be careful though because there would be little room for profitability if selling prices decrease or input prices increase. This scenario would also greatly benefit from marketing a premium product to help ensure positive margins.

A mid-scale plant requires coordinating with other feedlots to ensure the plant runs at capacity. Milner Ranch would have to find and incentivize various feedlot owners throughout the region to supply 19,000 cattle in addition to their 1,000 to ensure the plant would run at capacity. They would have to be competitive with the existing prices paid for fed cattle by existing beef processing plants in the region. If Milner Ranch wishes to sell the meat as a premium product, they would need to additionally establish and incentivize production practices consistent with higher standards from the birth through feeding. This would require either contracting or forming a co-op with other feedlots. Finally, the up-front cost of a plant this size is estimated to be $34.2 million. Milner Ranch has up to $4 million of financial capital on hand but would need to acquire the rest through a business loan or shared ownership with other co-op members.

4.2 What Type of Relationship Should Milner Ranch Processing Plant Maintain with Feedlots?

Jack recognizes that ensuring the processing plant runs at capacity will be key for maintaining profitability. This is going to depend upon Milner Ranch's ability to acquire quality finished cattle in a timely manner. The ability or inability of Milner to achieve this will depend upon the relationship they have with their suppliers. He has narrowed this decision down to three possibilities.

1. **Owner Fed Plant**: Milner Ranch supplies its own cattle to a small-scale plant.
2. **Marketing Contracts:** Milner Ranch acquires the 19,000 additional cattle they require through marketing contracts that specify price per pound and various bonuses/penalties based upon meat quality/attributes.
3. **Co-op Plant:** Milner Ranch starts the plant as a co-op for cattle feedlot owners. Milner would be a 5 percent owner because they would provide 5 percent of the total cattle to run the plant. They would find other feedlots within the region that they would share all costs and profits with evenly, provided cattle were meeting all pre-specified quality expectations.

4.2.1 Owner Fed Plant

The advantageous part of this particular plan is its simplicity. Milner Ranch doesn't have to shop around for more cattle or convince other feedlots to buy into their vision of best feedlot practices. Since both the feedlot and processing plant are housed within the same company, coordination would be easy. What will also help them maintain a low transportation cost for acquiring cattle is that both operations would be housed at the same location. This plan would synergize best with a small-scale processing plant because Milner Ranch would have to scale up its feedlot dramatically to supply enough fed cattle for a mid-size plant with only its own cattle. This degree of scale-up is not something they currently are interested in pursuing.

This plan puts a lot of pressure on Milner Ranch's cow-calf, grazing, and feedlot operations. If at any point those operations are not producing the amount of cattle they are supposed to, they risk their plant not running at capacity, which will lose them money. This marketing arrangement only works with a small-scale plant, so Milner Ranch would have to contend with the relatively higher production costs associated with a smaller plant.

4.2.2 Marketing Contracts

Marketing contracts between feedlots and beef processing plants are the industry standard. This arrangement would allow Milner Ranch to add value to all of their finished cattle while allowing for economies of scale that come with a mid-sized operation. This would allow them to take a cut of the

marketing bill for all of the additional cattle they contract with. There would also be some logistical advantages for getting their packaged meat to wholesalers, retailers, and/or restaurants.

Under this scenario, Milner Ranch would bear the entire cost of a 20,000 head per year processing plant by themselves. They have enough resources to put 10 percent down and obtain financing for the rest, but it would spread finances pretty thin. Their loan would come from a local bank with 8 percent interest, to be paid back over fifteen years. The marketing contract scenario exposes Milner Ranch to the most risk because they would pay for the entire processing operation. The marketing contract scenario also requires monitoring quality of purchased cattle. Milner Ranch has to write and enforce contracts carefully to ensure that they are getting the type of cattle they want to achieve premium high-quality beef.

4.2.3 Co-op Plant

This arrangement would allow Milner Ranch to reap many of the benefits of a mid-size processing plant without having to pay the full cost of one. They would be in charge for 5 percent of the purchase price and operating costs of the plant, with the other 95 percent being paid by other co-owners. They would pay their share of up-front fixed costs ($1.71 million) with their own capital. Member feedlot incentives may be more closely aligned in this arrangement than under marketing contracts since everyone who provides cattle will share in the profits from processing.

Under this scenario, Milner Ranch would only receive 5 percent of the profits of this plant because they are 5 percent owners. They would also give up a significant amount of control since they are only partial owners. The co-op plant scenario would require considerably more negotiation and back and forth than the other two arrangements, raising transaction costs. Co-ops are also only as strong as their weakest members, so recruiting others with similar quality concerns and work ethic is critical for this venture.

4.3 Should Milner Ranch Even Build a Processing Plant?

After coming up with the size and transactional relationships likely to be the best options, it is worth asking the final question, is the best option better than business as usual or a minor modification? Milner Ranch is already profitable and is under no obligation to build any kind of processing plant. While processing constraints and supply chain disruptions from COVID-19 shutdowns motivated some of Milner Ranch's conversations, processing has mostly returned to normal. Instead of considering a processing plant, they could instead take that money they would have spent vertically integrating their operation and expand or enhance the business in other ways.

4.4 Future of Cattle and Beef Prices

Another important question to think about in making a recommendation is how is the market likely to evolve over time? This plant will operate for several decades, and the current prices Milner Ranch is responding to will almost assuredly not be the same in the future. While Jack doesn't have a crystal ball, a little bit of critical thinking and basic economic analysis may help him determine if beef processing is likely to become more or less profitable over time. Here Jack thinks about the two most important variables to meat processing: fed-cattle prices (input cost) and beef prices (output price), and what could potentially happen with them over the life of the investment.

4.4.1 Steady Margin Scenario

In this scenario, cattle and beef prices follow the typical boom-bust cycle, but real margins remain stable and similar over the long term. After some research and consulting, Jack thinks that this scenario will be the most likely over the life of the plant. This scenario becomes even more likely when one realizes that cattle price and beef prices are positively and highly correlated. This correlation makes large margins

unlikely, but it also lowers the probability of negative margins. Jack thinks that this scenario has a 50 percent probability of occurring in the long term.

4.4.2 Best Case Scenario

Under the scenario, continued expansion in population and income growth increases the demand for beef. Risk and regulations keep the supply of new beef processing plants constrained, limiting competition. If this occurs, Jack expects beef prices to increase in real terms (2 percent annually). On the cattle side, improvements in genetics and management practices increase herd sizes, and the price for fed cattle remains steady in real terms. In this scenario, a processing plant would see a modest improvement in its margins each year. Jack sees this scenario as somewhat, having a 25 percent probability of occurring.

4.4.3 Worst Case Scenario

Under this scenario, meatless substitutes to beef continue to increase in quality and decrease in price. This increased competition lowers real beef prices by 1 percent annually. Housing development combined with climate change reduces available rangeland for cattle grazing and increases grain prices. Increases in government regulation on cattle production further drive up the cost of producing cattle. These changes in turn increase the price of fed cattle by 1 percent annually. Jack sees this scenario as being somewhat likely to occur and ascribes a 25 percent probability to this outcome occurring.

The real world is a little messier than having three discrete and well-defined scenarios. It could be any combination of steady prices, price increases, or price decreases for fed cattle and beef prices. The general ideas of steady margins, best or worst scenarios, helps highlight in which way the profitability for the industry may move in the future. Movements of both prices in the same direction would likely fall into the steady margin scenario, even if both prices greatly change; as long as margins remain similar, the plant will maintain similar levels of profit over time.

5 Milner Ranch Strategy Questions

5.1 Reflection

As Jack weighs his options for the upcoming meeting, he marvels at how complicated an initially simple decision of processing plant vs. no processing plant has become. He now has four realistic options: no processing plant, small-scale plant fed with only Milner Ranch Cattle, mid-scale plant with marketing contracts, and a mid-scale plant formed as a co-op with other feedlots. Each of these options is complicated by the fact that Jack sees three plausible future states of the world: steady prices, increasing prices, and decreasing prices for fed cattle and beef, respectively. Either of these variables could have a huge impact on Milner Ranch's best option to follow.

Over the past two decades, Jack has helped build Milner Ranch into a successful and profitable business. Even more impressively, he has done it while staying true to Milner Ranch's vision. Jack has to make big decisions and take more than a few risks to make Milner Ranch profitable. A successful processing plant could further enhance Milner Ranch's brand, reach, and profitability by allowing them to highlight their cattle. On the other hand, an unsuccessful processing plant could significantly impact the other two divisions of the operation. He wonders if it is worth one more dice roll to take the company to the next level or if it is time to start playing a little safer and make smaller changes with less of a potential payoff.

5.2 Discussion

Setting Up and Modeling the Problem

1. Sketch out a SWOT analysis of Milner Ranch's current operation. Pay careful attention to list the internal factors that they have control over (strengths and weakness) as well as the external factors currently affecting the operation that are beyond their control but they must respond to (opportunities and threats). Once you complete the baseline SWOT analysis, conduct a SWOT analysis for each of the three strategies under consideration. Use these four SWOT analyses to inform your answers to discussion questions 3–10.
2. Conduct a PESTEL analysis of the most important external factors Milner Ranch would likely face if they invest in a beef processing plant. Come up with at least one example for each category. Use this PESTEL analysis to inform your response to discussion questions 3–10.

How large should a potential processing plant be?

1. Would a small or mid-size plant be more likely to be successful?
2. What are the two greatest benefits of the plant size you chose?
    a. Explain why you think these benefits are the most important.
3. What are the two greatest costs or risks associated with the plant size you chose?
    a. Explain why you think these costs or risks are the most important.

What type of relationship should a Milner Ranch processing plant maintain with feedlots?

1. What are the two greatest benefits of the relationship you chose?
    a. Explain why you think these benefits are the most important.
2. What are the two greatest costs or risks associated with the relationship you chose?
    a. Explain why you think these costs or risks are the most important.

Should Milner Ranch even build a processing plant?

1. After considering potential future factors that could affect the fed-cattle and beef prices, do you personally think it will be easier or harder to make money with a beef processing plant in thirty years than today? Why?
2. What is Milner Ranch's opportunity cost for building a processing plant?
3. After considering the best possible size, transactional relationship, predicted trend of the industry, and opportunity cost, would you make this investment? Why?
4. What other strategies could Milner Ranch follow to make their overall operation more profitable?

About the Authors: Hwangwo Lee was a Masters Student at Utah State University and is now a PhD student at the University of Georgia. Tanner McCarty is an Assistant Professor at Utah State University (Corresponding author: tanner.mccarty@usu.edu). Anastasia Thayer is an Assistant Professor at Clemson University. Ryan Larsen is a Professor at Utah State University.

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Case Study

Hedonic Price Analysis of Used Tractors

Ryan Feuz
Utah State University

JEL Codes: A22, A23, D12, Q13
Keywords: Hedonic regression, misspecification, ordinary least squares, tractor prices

Abstract
This case follows Nate Shepard, a fictionalized data analyst for John Deere, as he is tasked with finding a suitable method for predicting used tractor prices. Nate uses hedonic price theory to specify and estimate a regression equation that can be used to evaluate marginal values of specific tractor attributes and predict out-of-sample tractor prices. Beyond price prediction, Nate must also consider the inflationary environment the used tractor market has been experiencing of late in his regression specification as well as compare the John Deere brand to rival manufacturers. The case allows readers to go along with Nate in the journey as he completes the process of data collection and cleaning, initial model specification based on relevant literature and theory, model estimation, evaluation of the model for misspecification issues, model revision and re-estimation, and model interpretation and use. The case provides an excellent example of empirical regression analysis in an agribusiness setting and gives readers an opportunity to familiarize themselves with hedonic price theory using a data set of actual used tractor auction results from 2020–2022.

1 Introduction

As a recent graduate in agricultural economics from the University of Illinois, Nate Shepard was excited when he landed his first job out of school as a Market Analyst for John Deere. The job was everything he hoped for. It was based in his hometown and location of John Deere company headquarters, Moline, Illinois. As the job title suggests, it was an analytical position with an opportunity for Nate to work on empirical analysis, which played to Nate's strong suite at working quantitatively. Most important, however, the position allowed for Nate to remain connected with the agricultural industry. Nate grew up on a family farm just outside of Moline producing mainly soybeans and corn. Nate enjoyed life on the farm, yet for a variety of reasons continuing to work on the farm post-college was not a viable option for him.

Nate was hired at an interesting time in the agricultural industry as well as within the company. The world was emerging from the global COVID-19 pandemic, which brought a host of challenges and opportunities to the economy at large and the agricultural industry. Notable challenges included the Ukrainian invasion by Russia, farm labor shortages, ongoing and persistent drought, as well as inflation and rising input costs. John Deere was in the middle of a great year. The company had reported net income of just under $6 billion for 2021, and forecasts indicated that 2022 was on pace to increase net income to $6.5–7 billion for 2022 (John Deere 2021). John Deere CEO, John May expected "demand for farm and construction equipment to continue benefiting from positive fundamentals, including favorable crop prices, economic growth, and increased investment in infrastructure" (John Deere 2021). At the onset of Nate's employment with John Deere, his manager, Todd Smith, assigned him a task with an objective that Nate recognized would require the use of much of his quantitative analysis skill set he had acquired through his schooling. Todd walked Nate through the problem and the objective.

> "*Throughout the last few years, the company has seen strong sales and an increase in demand in our agricultural tractor division,"* Todd said*. "However, one issue we face is continued supply chain disruptions and their associated impact on sales. Pandemic-related disruptions as well as the labor strike the company faced in the fall of 2021 lead to significant reductions in output for the company in the fourth quarter of 2021 and first quarter of 2022* (Tita 2021)*. This reduction as well as simultaneous reductions in supply by our competitors mainly due to COVID-19–related disruptions formed a chain reaction ultimately pushing used tractor prices upward* (Deaux 2021)*."*

Nate was keenly aware of this increase in used farm equipment prices, having just been through the purchasing process of a used tractor at an auction for the family farm with his dad. Nate relayed this purchasing experience to Todd and described the financial difficulty it created for their farm as they paid approximately 90 percent the original retail price for the used tractor, despite it being three years old with nearly 800 hours of use. Todd sympathized with Nate and then proceeded to lay out the objective of the project he wanted Nate to work on.

> "*Your family's experience unfortunately was not an isolated incident as I have heard several other firsthand accounts similar to yours from friends and family of late. Deere is committed to continual improvement of our supply chain to help ensure these disruptions can be avoided in the future. However, for the time being, we are very interested in an analysis of the used tractor market to help us better understand three things. First, how can we more appropriately advise our dealerships on pricing used tractors that we take in on trade. Second, regarding brand, how has the John Deere brand specifically been fairing relative to our competitors in the used market. Third, how much have used tractor prices been hit with inflation. I would like for you to perform a detailed analysis of the used tractor market over the last three years to help answer these questions. I will present your analysis to our upper management team and distribute the information across our dealer network*."

Todd provided Nate with no specific method of analysis, leaving that to Nate's discretion as to best accomplish the objectives that he had laid out for him. After receiving this directive, Nate reflected on the opportunity that was before him. Nate recognized that this was an ideal project for him to work on because he could leverage many of his newly acquired analytical skills from his time at the university and have a chance to have his work distributed broadly within the company, which could lead to greater opportunities for growth and recognition in his new position. It was time to get to work!

2 Data: Clean Up, Visualization, and Initial Analysis

The beginning of any successful analytical project begins with quality data. Nate wanted to focus his analysis on the last three years because he felt this would capture the years of an increased rate of inflation. After consulting with Todd, Nate also decided to constrain his analysis at least initially to used tractors within the 40–99 horsepower (hp) range that were equipped with a loader. This would be an important constraint as Todd was certain that when comparing price variance between smaller tractors versus large commercial size tractors there would be differences in the values that producers placed on certain attributes of the tractors themselves. For this reason, Nate felt if he didn't constrain his analysis to a specific horsepower class, his predictive accuracy would decline. The aims of the project required that the data include actual sale prices for used tractors in this hp class across the entire United States. Nate decided to rely on publicly available auction result data from TractorHouse.com. Before pulling the data from the site, Nate constrained the results to the appropriate hp range, U.S. sales only in the last three years, model years 2010 or newer, loader included, and only tractors from the top manufacturers,

including John Deere, Case IH, Kubota, Mahindra, Massey Ferguson, and New Holland. Altogether, Nate's data set comprised 1,103 observations of tractors sold at auction.

With the data in hand, the next step was to look at summary statistics and scatterplots of the data to identify possible outliers and data entry errors. Nate first created a scatterplot (Figure 1) with sale prices on the *y* axis and hours (usage hours) on the *x* axis.

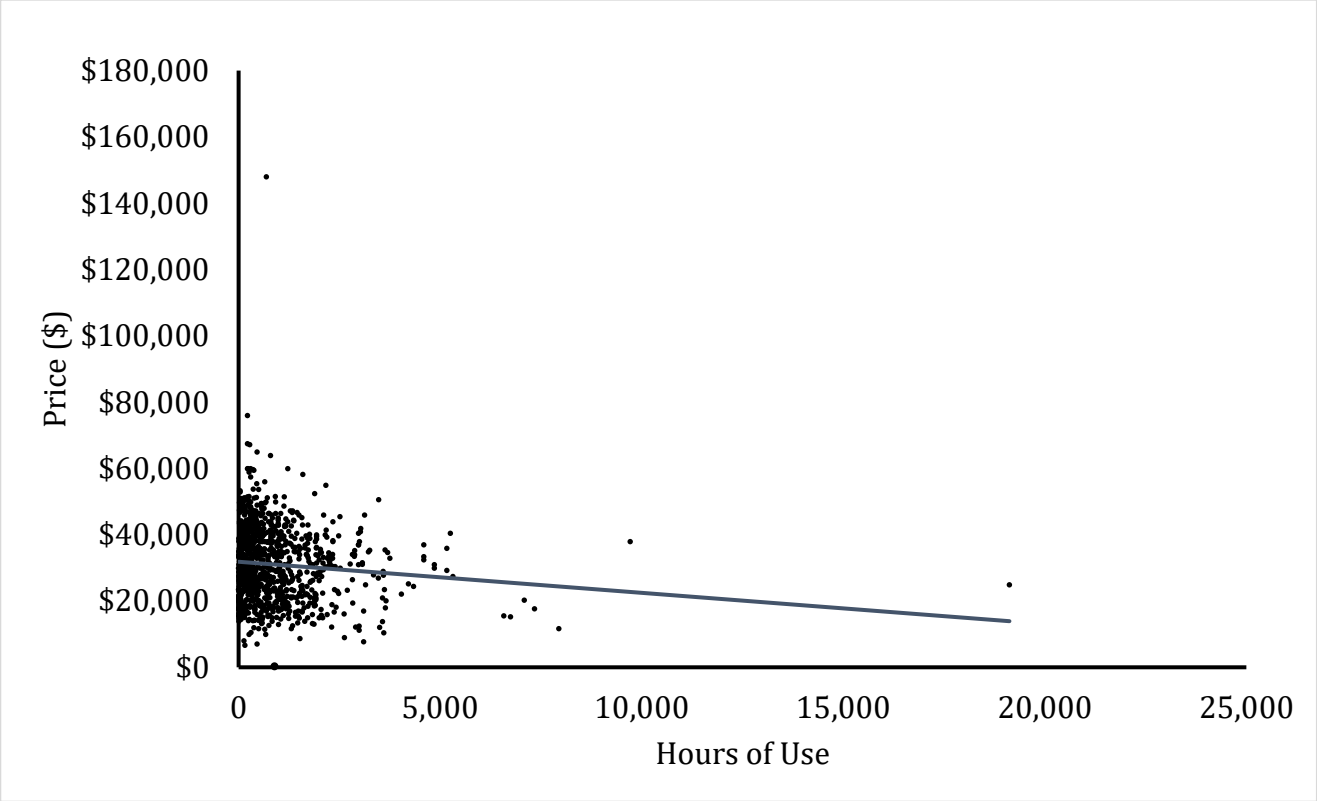

Figure 1. Tractor Sale Price versus Hours of Use

Hours on a tractor is an indicator of total usage, and Nate was confident that hours of use should be negatively correlated with sales price. As Nate looked over the scatterplot, he noted that there was indeed a negative correlation between these variables as indicated by the included trendline. From the graph, Nate was alarmed by three outliers. First, the highest auction price was recorded at nearly $150,000 whereas all other prices were below $80,000. Second, the lowest price was recorded at $227 whereas the next lowest was at $4,730. Third, the highest hours were listed at nearly 20,000 with the next highest at approximately 10,000. As Nate looked closely at the data, the hours outlier was easily identified as a data entry error. The hours were recorded as 19,122 in his data set as well as one location on the specific tractor advertisement. Yet in the written description in the online advertisement, the hours were stated as approximately 9,800. With no way to verify the correct hours, Nate decided it was best to eliminate this tractor from the data set for his analysis. Though not as clear-cut, Nate ultimately decided the high-priced tractor of nearly $150,000 and low-priced tractor of $227 were also presumed data entry errors. Nate determined this by comparing the sales prices of the other tractors of the same makes and models. The average sale price for the high-priced make and model (John Deere 5075E) across 74 total tractor sales was $34,513, with the maximum price at $51,000 and the low price at $11,750. There was only one other tractor of the same make and model as the low-priced tractor (New Holland T5050), and it sold in the same month and year for $33,500. Nate found nothing in the

advertisement of the low-priced tractor that would suggest it had any reason to be sold at such an extremely low price.

For these reasons, Nate concluded that it was unreasonable for tractors of these makes and models to sell at these extreme outlier prices and felt it was best to remove them from the data set, leaving him with 1,100 observations for his analysis. With the outliers removed, Nate knew the average predictive accuracy of his future analytical model would improve. As predictive accuracy was one of the goals that Todd had laid out for him, he felt removing the outliers was the appropriate action.

After finishing a further evaluation of data scatterplots with other variables included, Nate was confident he had addressed outliers adequately. He then summarized all the variables in the data set in a table of summary statistics (Table 1).

Table 1. Data Summary Statistics

	Price	Hours	hp[a]	Rear Remotes[b]	Cab[c]	Air[d]	Heat[e]	Repair/Salvaged[f]
Average	$30,806.29	843	65	0.88	0.47	0.37	0.26	0.05
Standard Deviation	$10,756.50	1022	17	0.94	0.50	0.48	0.44	0.22
Minimum	$4,730.00	0	40	0	0	0	0	0
Maximum	$76,000.00	9717	99	4	1	1	1	1

Notes: Total sample size *n* = 1,100 with six tractor makes: John Deere = 450, Kubota = 203, Mahindra = 155, New Holland = 148, Case IH = 76, and Massey Ferguson = 68.
[a] hp = tractor engine horsepower.
[b] Rear Remotes = the number of rear remote auxiliary hydraulics.
[c] Cab = is an indicator variable equal to 1 if the tractor has a cab and equal to 0 otherwise.
[d] Air = is an indicator variable equal to 1 if the tractor has air conditioning (AC) and equal to 0 otherwise.
[e] Heat = is an indicator variable equal to 1 if the tractor has heat and equal to 0 otherwise.
[f] Repair/Salvaged = is an indicator variable equal to 1 if the tractor requires major repairs or has been categorized as a salvage only vehicle and equal to 0 otherwise.

In addition to the sale price and hours of usage, the data set also included variables for the tractor make/model, engine horsepower, and the number of rear remote hydraulics. From the tractor advertisement descriptions, Nate was also able to create four additional variables that he felt could be useful in his analysis. These variables included *Cab, Air, Heat*, and *Repair/Salvaged* and were all created as indicator (dummy) variables. An indicator variable can be coded in various ways but most often takes on the value of 1 for any observation that includes the specific trait suggested by the variable name and 0 otherwise. Thus, for example, Nate placed a one under the variable *Cab* in his data set for any tractor observation that was described as including a cab. If a tractor did not include a cab, Nate placed a 0 under the *Cab* variable for that observation. He created the variables *Air*, *Heat*, and *Repair/Salvaged* similarly by observing from the ad descriptions if tractors included air conditioning (AC) and heating, or required significant repairs (or classified as salvage only). After creating the summary statistics table, Nate reflected on what he could learn from the table.

> "*My total sample of 1,100 observations should be adequate for my analysis, and it's good to see that I have many observations for each of the various tractor makes (John Deere = 450, Kubota = 203, Mahindra = 155, New Holland = 148, Case IH = 76, and Massey Ferguson = 68). This should allow me to make good comparisons across tractor makes. I also have good variability within the other variables. The averages of my indicator variables (Cab, Air, Heat, and Repair/Salvaged) let me know the proportion of my sample that have the characteristics indicated by the variables, so 47 percent of the tractors in the data set have a cab, 37 percent of those cabs have AC, and 26 percent are heated. I would think that having a cab and*

AC/heat would be correlated with higher auction prices. Many of the tractors that have AC will also have heat, and if a tractor has either AC or heat, it will naturally also have a cab."

Nate took a mental note that this relationship between *Cab*, *Air*, and *Heat* suggests that they are correlated with each other and could present difficulties in his analysis. He would revisit this topic as he progressed with the statistical analysis. Nate also noted from his *Repair/Salvaged* variable that only 5 percent of the tractors needed significant repairs or were salvaged.

"*I bet these tractors are highly negatively correlated with price,"* he thought. *"Before moving to more advanced statistical methods, I should evaluate the conditional average auction prices for various tractor attributes*."

Nate had worked extensively with Microsoft Excel (Microsoft Corporation 2018) managing data sets during his time at school and felt confident in his ability to quickly create a summary table of conditional average prices and average horsepower using pivot tables. Nate created the table (Table 2) to display the conditional average price and horsepower for each of his indicator variables as well as for each of the tractor makes. These conditional averages helped Nate quickly identify the direction of the relationship between these variables and the auction prices as well as make comparisons between the levels within a variable. Comparing the conditional average prices between the various tractor makes, Nate found that within his data set Case IH tractors sold for the highest average price ($34,473) followed closely by John Deere ($33,953). The Mahindra tractors sold for the lowest average price at $21,980, with all other makes right around $30,000. These findings were not surprising to Nate, as he felt John Deere and Case IH had long been held in high regard as quality brands that command top-dollar prices. Mahindra on the other hand is the top tractor manufacturer in the world (Tractor Junction 2022) and specializes in producing quality tractors at an affordable price. Nate also knew that Mahindra had a

Table 2. Conditional Average Tractor Prices by Variable Levels

Variable	Level	Price	Horsepower
Make	Case IH	$34,473	71
	John Deere	$33,953	67
	Kubota	$29,828	62
	Mahindra	$21,980	56
	Massey Ferguson	$30,064	72
	New Holland	$30,282	69
Cab	Yes	$36,337	62
	No	$25,901	70
Air	Yes	$36,113	63
	No	$27,738	70
Heat	Yes	$35,817	64
	No	$29,021	69
Repair/Salvaged	Yes	$19,074	66
	No	$31,447	59

strong presence in the lower horsepower tractor market in the United States and thought that the lower average price could also be influenced by a lower average horsepower of the Mahindra tractors in the

data set. Returning to his pivot table, he found that the average horsepower of the Mahindra tractors was 56 as compared to the average of the other makes ranging from 62 to 72.

This analysis of conditional averages demonstrated an important principle that Nate had learned while in school. The analysis showed that the Mahindra tractors had the lowest average price but also the lowest average horsepower. Thus, it was impossible to tell if the price was lower on average because of the quality effect of the manufacturer or if the price was lower simply due to the lower average horsepower. Nate assumed the answer was some combination of the two possibilities but knew that other variables also had an effect on price that were not included in this analysis of conditional means. For example, Nate suspected that tractors sold without a cab were cheaper than those with a cab, but having a cab may also be correlated with horsepower, make, and so on. Given the objective from Todd, Nate knew it would be important for him to estimate the marginal effects on the auction price of the variables while holding all else constant. The marginal effects would provide John Deere with marginal values of various tractor attributes for the used tractors that the dealer network took in on trade. The marginal values in turn could be used to better price those used tractors for the resale market.

3 Hedonic Price Analysis

To take his analysis to the next level, Nate needed to calculate the marginal values of a used tractor's attributes on the total auction price. Nate recalled the theory and techniques he had learned in his advanced agricultural marketing course at the university concerning hedonic price theory. At its core, hedonic price theory states that the total value of a good is equal to the sum of the values of its individual attributes. Court (1939), in his paper which created a hedonic pricing index for automobiles, is often credited as being the first to demonstrate the basic principles of hedonic analysis (Goodman 1998), though he did not formalize the theory. While several other researchers used a similar approach following Court (1939), it was not until 1966 in Lancaster's seminal paper on consumer theory where hedonic theory began to take form. Lancaster (1966) broke away from the traditional consumer theory at the time wherein it was assumed that goods were the direct objects of utility. Instead, Lancaster suggested that the total utility derived from consumption of a good could be decomposed into the utility provided by the individual characteristics or attributes of the good. Lancaster's work focused on how consumers make decisions given a choice set of goods, each providing utility equal to the sum of their individual attributes. Thus, there was no connection between Lancaster's new consumer theory and the market equilibrium or pricing. This gap was filled in 1974 when Rosen formalized the theory that a good's market value (price) can be decomposed into a sum of the individual values of its utility generating attributes. Rosen (1974) demonstrated how this theory could be applied in a hedonic regression analysis by using a good's price as the dependent variable regressed upon variables indicating the good's attributes to determine the way in which each attribute uniquely contributes to the price. Not only could such a regression analysis provide these marginal values of the attributes of a good, but the resulting estimated regression equation could be used to predict prices for a good based on the sum of its parts. For example, hedonic regression is often applied to housing markets to predict the price of a house based on the individual value of its attributes such as square footage, number of bedrooms, number of bathrooms, and so on. Nate felt hedonic regression analysis would be the ideal method for him to be able to accomplish the objectives given to him by Todd.

Before estimating any regression equation, Nate knew the importance of defining the equation to be estimated as well as forming a hypothesis for the sign of each variable included. Nate had been taught that this was an important step in the research process for a couple of reasons. First, clearly defining the regression equation to be estimated can help reduce p-hacking tendencies, that is, the tendency for researchers to collect and analyze data in such a way to represent statistically significant effects when there may be no real underlying effect at all (Head et al. 2015). One questionable data practice that contributes to p-hacking is adding or removing variables to regression equations in an attempt to

increase the goodness of fit while ignoring theoretical considerations for inclusion or deletion of variables. Second, forming an educated hypothesis of the sign of each variable before estimation can help the researcher evaluate the equation post-estimation and identify possible problems with the model.

3.1 Previous Literature

One of the best methods to establish which variables should be included in a regression equation is to reference published literature with similar objectives to identify the consensus and theoretical implications for inclusion/exclusion of specific variables. Nate scoured the literature to gain better understanding of what variables he should include in his model. One of the earliest studies Nate found was Fettig (1963). Noting Court's 1939 study estimating hedonic price indices in automobiles, Fettig (1963) applied similar methodology to the tractor market. Fettig's (1963) regression equations predicting new tractor prices included horsepower as well as an indicator variable for whether the tractor was diesel powered (as opposed to gasoline). Fettig considered numerous other variables such as fuel efficiency, maximum pounds of pull, miles per hour at maximum drawbar horsepower, and weight of the tractor. However, Fettig ultimately excluded these other variables from the analysis because they were not statistically significant or were highly correlated with horsepower and provided no additional explanatory power. Fettig noted that tractor prices could vary substantially due to tractors various attachments (e.g., fast hitches, remote hydraulics, power steering, independent power takeoffs, etc.). To control for such variables without explicitly including them in the regression, Fettig adjusted the prices to strip tractors of added attachments or add-ons. Using these stripped prices as the dependent variable and the two explanatory variables, horsepower and diesel, the regression equations estimated for years 1950–1962 were able to explain approximately 87–95 percent of the variation in tractor prices. This percentage of the variation of the dependent variable explained by the models was indicated by the range of R-squared values.

Berck (1985) used a data set that could be characterized as mixed time series, cross-sectional. From this data set, he estimated a single hedonic regression equation for tractors for the years 1923, 1930, and 1933. His objective was to determine the value of technical progress over these years by estimating the values attributable to quality (attributes of the tractors) with the remaining difference attributed to technical progress. He included horsepower as well as indicator variables for the year in which the tractors were sold. He considered fuel efficiency but ultimately removed this variable because it was not found to be statistically significant. The resulting regression equation had an R-squared of 0.84, which Berck concluded was quite good considering the time series, cross-sectional nature of the data set.

Nate felt both previous studies provided a good foundation for him to begin his own hedonic tractor analysis, but they only analyzed new tractor prices and they were both very old studies. Nate knew that just as Fettig (1963) noted, tractor prices would undoubtedly vary greatly due to equipped add-on attachments. Stripping the tractor prices of the values of these add-ons allowed Fettig (1963) to control for them. Nate would not be able to make such an adjustment. His analysis was for used tractors that included a loader. However, beyond loaders, each tractor may or may not have been sold with other additional add-ons. Nate needed to find a more recent study with used tractor prices to see how best to control for known add-ons or features. In his research, Nate found just such an article by Diekmann, Roe, and Batte (2008). These researchers used hedonic regression to compare used tractor prices for tractors sold on ebay.com (online auction website) versus at in-person auctions. They pooled the tractor sales data from both ebay.com and in-person auctions and included a dummy variable in the model for type of auction. They then included a host of explanatory variables designed to account for quality differences in the tractors, many of which were associated with add-ons. These variables include horsepower, age, diesel/gas, implement/no implements included, manual/automatic transmission, four-wheel drive/two-

wheel drive, tractor make indicator variables, sold on weekend/weekday, and monthly seasonal dummy variables. In addition to these variables, the researchers also included squared variables for hours, horsepower, and age. Including them in this manner allowed for their effects to take a nonlinear form (increasing/decreasing at an increasing/decreasing rate). These researchers also evaluated additional functional forms of the regression equation and relied upon an endogenous switching regression. Their final model explained 83 percent of the variation in their used tractor auction prices as indicated by the R-squared value.

After considering the literature and theory, Nate specified his initial regression equation to be estimated as:

$$P_i = \alpha_0 + \beta_1 Year_i + \beta_2 Age_i + \beta_3 Age_i^2 + \beta_4 hp_i + \beta_5 hp_i^2 + \beta_6 Hours_i + \beta_7 Hours_i^2 + \sum_{j=8}^{13} \beta_j Make_i + \beta_{14} Air_i + \beta_{15} Heat_i + \beta_{16} Cab_i + \beta_{17} R\_Hyd_i + \beta_{18} Auto_i + \beta_{19} 2WD_i + \beta_{20} Rep\_Sal_i + e_i \quad (1)$$

where P_i is the auction sale price of the ith tractor; *Year* is the year in which the tractor was sold (2020, 2021, or 2022); *Age* is the tractor age in years; *hp* is horsepower; *Hours* is hours of usage; $Make_i$ represents five dummy variables included for manufacturer of the *i*th tractor (John Deere omitted as the reference base); *Air*, *Heat*, and *Cab* are all dummy variables equal to 1 if the tractor includes AC, heat, or a cab, respectively, and equal to 0 otherwise; R_Hyd the number of rear hydraulic remotes included; $Auto$, $2WD$, and Rep_Sal are dummy variables equal to 1 if the tractor has an automatic transmission (i.e., hydrostatic or continuously variable transmission); two-wheel drive or needs repairs/salvaged, respectively, and equal to 0 otherwise; and e_i is the stochastic error term assumed to be normally distributed with a mean of 0 and constant variance.

Nate ran over the variables quickly in his head to think about his hypothesized signs for each.

> "***Year**, I would expect to be positive as we have seen tractor prices inflating over the last few years. **Age**, on the other hand, I would expect to be negative as older tractor models I would expect to be correlated with lower auction prices. Horsepower should take on a positive sign as higher horsepower tractors should command higher expected prices. **Hours** should be negative since more hours indicates increased usage, which in turn would decrease the life expectancy of a used tractor. Since my dummy variables for make are all going to be relative to 'John Deere,' I believe they will all possess negative signs, with the possible exception of Case IH, which could be positive or negative depending on the effect of the other variables as the average prices of the tractors in the data set are very close for Case IH compared to John Deere. I do believe used John Deere tractors hold their value and sell for higher average prices relative to the other makes I have included in the data set. **Air, Heat, Cab**, and the number of rear hydraulics should all have positive signs as I believe buyers value these attributes positively. A tractor that is only two-wheel drive as compared to a 4×4 should be a lower value, so I would expect a negative sign for that variable. Finally, any tractor in need of repairs or classified as salvaged I would expect to be heavily discounted compared to those in good repair, so I would expect a negative sign on that dummy variable as well.*"

To reaffirm his hypotheses, Nate created scatterplots of the various explanatory variables on the *x* axis, with price on the *y* axis. Figures 2 and 3 contain the scatterplots of horsepower and hours, respectively. With a trendline added to these scatterplots, Nate was able to compare his hypothesized signs with the direction of the trendlines.

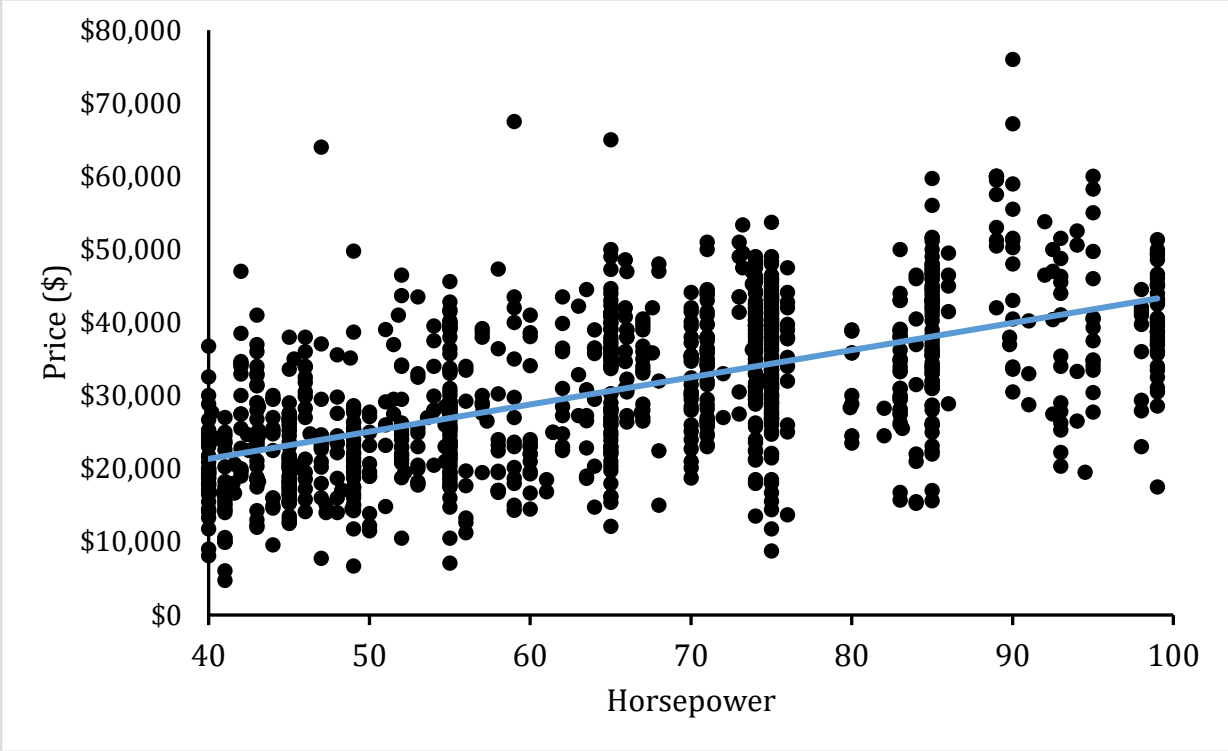

Figure 2. Price versus Horsepower Scatterplot

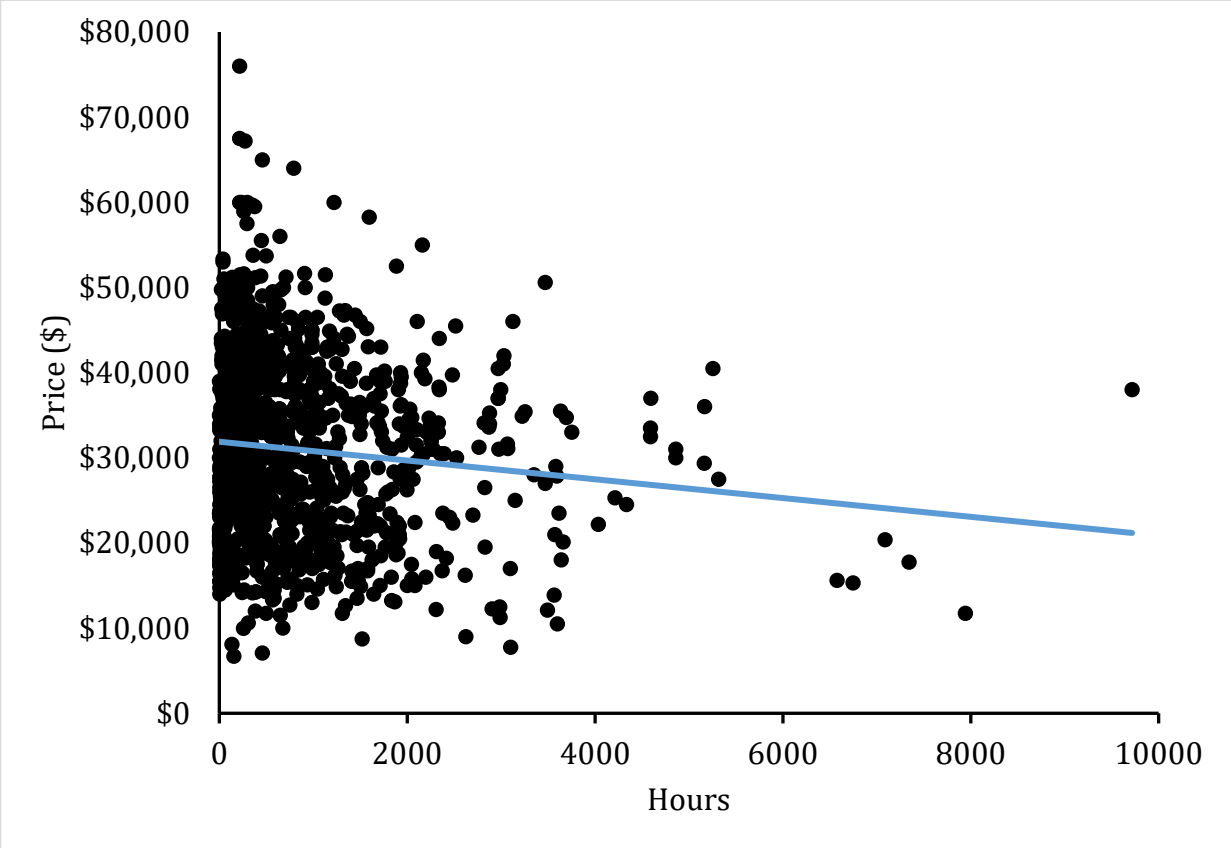

Figure 3. Price versus Hours Scatterplot

After completing the scatterplot analysis, Nate felt the next step was to estimate the regression equation and evaluate the results for potential problems or possible improvements. Nate estimated the regression equation using ordinary least squares (OLS) for Equation 1 on his computer; results are shown in Table 3.

Table 3. Initial Regression Results

Variable	Coefficient	Standard Error	*p*-Value
Year	2671.87	247.84	0.000
Age	-739.78	242.13	0.002
Age^2	19.12	19.68	0.332
hp	127.56	86.76	0.142
hp^2	1.61	0.64	0.012
Hours	-5.21	0.41	0.000
$Hours^2$	0.0004	0.0001	0.000
MAKES			
Case IH	-1856.85	687.34	0.007
Kubota	-2957.47	470.12	0.000
Mahindra	-10221.67	556.16	0.000
Massey Ferguson	-6018.95	731.47	0.000
New Holland	-4123.33	529.74	0.000
Air	466.67	710.51	0.511
Heat	221.57	611.84	0.717
Cab	7025.00	570.79	0.000
R_Hyd.	739.09	195.58	0.000
Auto	701.94	500.57	0.161
2WD	-3764.26	660.75	0.000
Rep_Sal	-4745.79	769.65	0.000
Constant	-5378111.00	500632.50	0.000

Note: All variables are as defined in Equation 1.
Adjusted R-squared = 0.7422
RMSE = 5,464
n = 1,100

Looking at the initial results, Nate had several takeaways—(1) the signs of all variables were as he hypothesized; (2) the negative sign on the *Age* estimated coefficient together with the positive sign on the Age^2 coefficient suggested that the effect of *Age* on price was one that was decreasing at a decreasing rate; (3) there was a similar decreasing at a decreasing rate relationship with *Hours*; (4) the positive signs on the *hp* and hp^2 coefficients suggested that the effect of *hp* on price was one that was increasing at an increasing rate; (5) all variables other than Age^2, *hp*, *Air*, *Heat*, and *Auto* were statistically significant at the 5-percent level (p value < 0.05); (6) the goodness of fit of the model as evaluated by the adjusted R-squared suggested that 74.2 percent of the variation in the used tractor auction prices could be explained by the variables included in the model, while 25.8 percent of the variation was left unexplained by variables not included in the model.

Nate felt that the results were reasonable. Although the adjusted R-squared was lower than those found in previous literature he had read, he was not surprised by this result. The studies he had read were quite dated. Tractors have seen large technological and mechanical advancements through recent

decades, which would suggest that capturing the variability in used prices would be much more difficult as the tractors could differ substantially in the attributes they now possessed. The R-squared was also lower than the more recent study he had reviewed of Diekmann, Roe, and Batte (2008). However, this too did not come as a surprise to Nate. These researchers had used regression techniques more sophisticated than OLS to help improve the goodness of fit. Nate was unfamiliar with the methods these researchers used and felt his simple model could still be useful to accomplish his objectives.

Before going further into the interpretation of the coefficients, Nate wanted to evaluate the model for common potential problems that arise in regression analysis.

3.2 Issues of Scale

Nate was initially concerned by the estimated value of the constant of -5,378,111. However, then he remembered how a constant can easily be manipulated to a more interpretable number by adjusting the scale of key explanatory variables. In this case, Nate recognized the *Year* variable as the one needing to be rescaled. Currently, it was not scaled at all, meaning if the tractor was sold in 2020, the value of the *Year* variable would be equal to 2020. However, because there were only three years contained in the data set (2020, 2021, and 2022), Nate recognized that if he rescaled the variable to be equal to the year the tractor was sold less 2019, the constant value could take on a more meaningful value while the marginal value for year would be left unaffected.

3.3 Multicollinearity

Multicollinearity refers to a problem that arises when two or more variables are highly correlated with each other. Independent (left hand side) variables as the name suggests should be independent of one another. When independent variables are highly correlated within a regression equation, it can reduce the precision of the coefficients of the correlated variables. Nate recalled his concern about the variables *Cab, Air*, and *Heat* being correlated. To evaluate the degree of multicollinearity within his variables, Nate calculated the variance-covariance matrix (Table 4). Nate had been taught a rule-of-thumb that any variables with a correlation coefficient of >0.7 could cause multicollinearity problems in a regression equation, and specification changes should be considered. Looking at the variance-covariance matrix, Nate identified, just as he expected, *Cab, Air*, and *Heat* as the only variables with a correlation coefficient >0.7. Nate considered what to do about his multicollinearity issue he had identified.

> "*I could simply omit variables **Air** and **Heat**. They are collinear with **Cab**, and judging by the initial parameter estimate for Cab, it appears to be much more influential toward price as having AC or heat,"* he thought.
>
> "*However, I do feel like people value AC and heat to some degree. Perhaps, if I combined the **Air** and **Heat** variables into one dummy variable that is equal to 1 when a tractor includes AC, heat, or both and equal to 0, otherwise this might resolve my multicollinearity issue*."

3.4 Heteroskedasticity

As Nate thought about other potential problems his model could have, he considered his error term, e_i as specified in Equation 1. Nate was using OLS as his estimator for Equation 1. The OLS estimator can have many desirable properties but only if the standard set of assumptions for this estimator are met. One such assumption is that the error term be normally and independently distributed with a zero mean and constant variance. Constant variance is said to be homoskedastic, whereas if the errors exhibit unequal variance the error term is said to be heteroskedastic (Kaufman 2013). One way to quickly evaluate

Table 4. Variance-Covariance Matrix for Variables Included in Initial Regression

Variable	Price	Year	Age	hp	Hours	Air	Heat	Cab	Auto	R_Hyd.	2WD	Rep_Sal
Price	1											
Year	0.21	1										
Age	-0.25	-0.07	1									
hp	0.58	0.01	0.07	1								
Hours	-0.10	0.02	0.44	0.31	1							
Air	0.38	-0.03	0.03	0.19	0.07	1						
Heat	0.28	-0.04	0.05	0.13	0.00	0.78	1					
Cab	0.48	0.00	-0.02	0.25	0.07	0.80	0.63	1				
Auto	-0.15	0.00	-0.02	-0.42	-0.08	0.00	0.02	0.02	1			
R_Hyd.	0.31	-0.02	0.07	0.38	0.11	0.22	0.23	0.19	-0.11	1		
2WD	-0.12	0.01	0.04	-0.03	-0.04	-0.10	-0.10	-0.11	-0.06	-0.05	1	
Rep_Sal	-0.26	-0.07	0.14	-0.08	0.03	-0.02	0.01	-0.05	-0.01	-0.06	0.03	1

whether a model suffers from heteroskedasticity is to plot the residuals against the fitted (predicted) values. Residuals are the difference between the actual values of the dependent variable and the predicted values. Nate created and evaluated the residual versus fitted values plot (Figure 4) for his hedonic regression equation. Nate recognized an undeniable pattern in his residuals right away. The cone-shaped pattern, as indicated by the blue lines Nate included in Figure 4, was a classic sign of heteroskedasticity within a model. The residuals exhibit a pattern of increasing in variance as the predicted prices increase in magnitude.

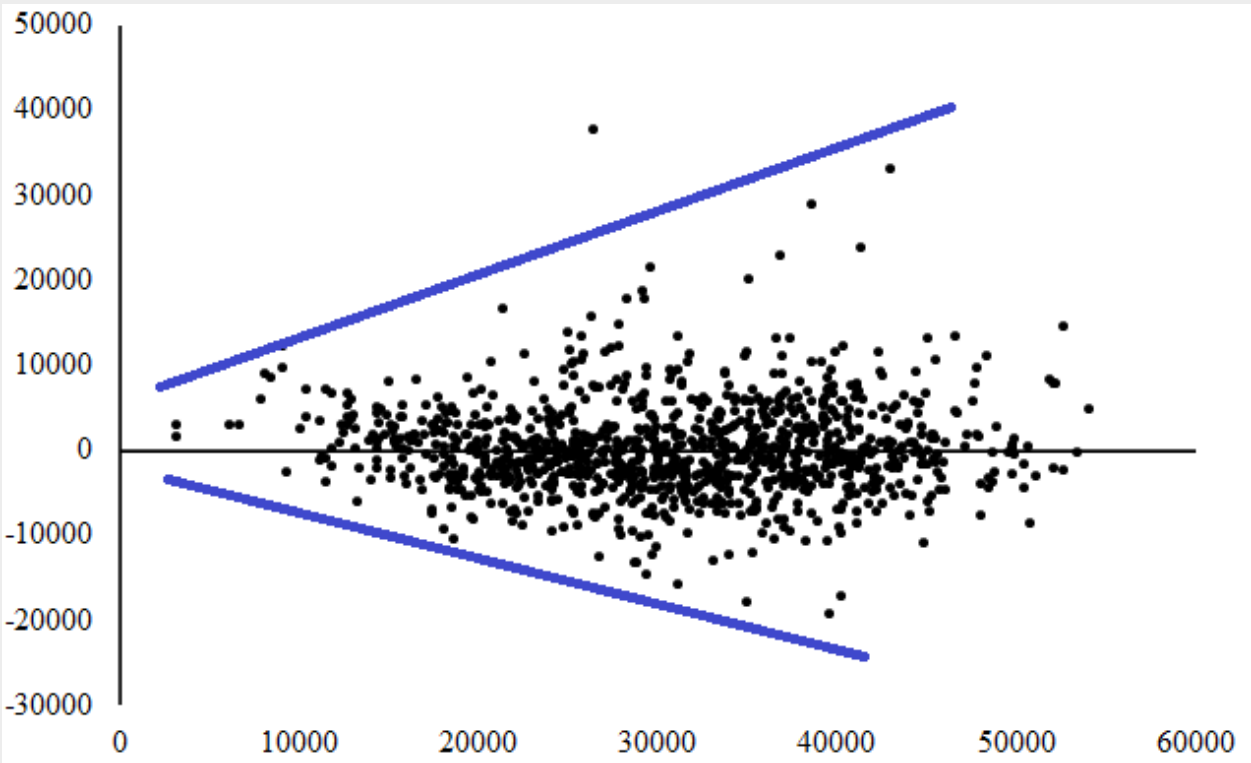

Figure 4. Residuals versus Fitted Values (Evaluation of Heteroskedasticity)

Nate recalled what he had learned about the problems with heteroskedasticity.

> "*For a model that meets all other assumptions of OLS, one with heteroskedastic errors will still produce unbiased coefficient estimates. This means I can still make good predictions with my model and can rely on the marginal values of the tractor attributes. But with heteroskedasticity, the standard errors of the coefficients will be biased. This means that unless I correct for the heteroskedasticity, I will not be able to make reliable statistical inferences from my results*." (Kaufman 2013)

Nate ran through the prescribed methods for addressing heteroskedasticity.

1) Transforming the dependent variable. This requires that a transformation be identified that is variance-stabilizing and has the downside of changing the scale of the dependent variable and complicates the interpretation of the marginal affects.
2) Use weighted least squares (WLS) in place of OLS. WLS is the optimal estimator for heteroskedastic data but requires the researcher to know or estimate the structure of the unequal variance.
3) Leave the heteroskedasticity in place but re-estimate the standard errors of the coefficients using a method that is robust to heteroskedasticity. The upside of this method is that no knowledge of what is causing the heteroskedastic errors is required, but a downside is that it is only suitable when working with large sample sizes because the OLS estimator will still be inefficient (Kaufman 2013).

Nate thought that some of the unequal variance could be proportionate to the horsepower variable. However, because Nate was unsure of the structure of the variance and his sample size was large (n = 1,100), he felt the best solution was the third method: use OLS with heteroskedastic robust standard errors estimated. This would allow for him to make correct statistical inferences about the significance of the explanatory variables without changing the parameter values estimated with OLS.

3.5 Irrelevant Variables

As Nate continued to look at his initial model results, he considered variables that may be irrelevant. Irrelevant variables can often be identified as those not statistically significant and not backed by theoretical reasoning. Inclusion of such variables has similar consequences as heteroskedasticity in that the coefficients estimated remain unbiased, but their variances are increased. This tends to understate statistical significance of the relevant variables included in the model (increases p values) and can lead to incorrect statistical inferences. As Nate considered the variables in his model, he felt that Age^2 fit the description of an irrelevant variable and determined that he would drop it from his final specification.

3.6 Variable Misspecification

One final problem that Nate considered was the possibility of variables being misspecified. He reflected on the specification of the *R_Hyd* (the number of rear hydraulic remotes) variable. Nate had specified this variable as a continuous variable. When he considered the values this variable could take on, he felt a change was in order. Looking over the summary statistics of his variables (Table 1), Nate noted that *R_Hyd* had a minimum of 0, a maximum of 4, and an average of 0.88. Although the variables average could be computed as any real number, the variable was discrete in that it only took on values from 0–4 in whole numbers (integers). Nate recalled from his schooling that discrete variables are often better represented through a series of dummy variables. Therefore, Nate determined he would remove the continuous *R_Hyd* variable and instead include three dummy variables *Rear1, Rear2, and Rear3.* These

variables would be equal to one if the tractor contained one, two, or at least three rear hydraulic remotes, respectively, and equal to zero otherwise. Including them in this manner would mean that the reference group would be tractors without rear remotes and the marginal values of these attributes would be interpreted relative to the reference group. Nate felt it was best to include tractors that had four rear remotes in the variable *Rear3* because upon inspection of the data, he found only three observations with four rear remotes included.

3.7 Final Model Results and Discussion

Nate made the changes to rescale the *Year* variable, account for the multicollinearity problem (combine AC and Heat), correct for heteroskedasticity (robust standard errors), drop irrelevant variables (Age^2), fix the misspecification of the rear remote hydraulic variable (change from continuous to discrete), and then re-estimated the regression equation (results in Table 5).

Table 5. Final Regression Results

Variable	Coefficient	Standard Error[1]	*p* Value
Year	2650.51	224.83	0.000
Age	-510.36	76.61	0.000
Age^2	172.30	89.68	0.055
hp	1.20	0.68	0.076
hp^2	-5.30	0.40	0.000
Hours	0.0004	0.00006	0.000
MAKES			
Case IH	-2103.92	683.99	0.002
Kubota	-3071.34	458.97	0.000
Mahindra	-10405.18	482.29	0.000
Massey Ferguson	-6086.24	714.00	0.000
New Holland	-4316.69	525.68	0.000
Auto	710.31	424.67	0.095
Air_Heat	766.89	619.29	0.216
Cab	6813.91	665.59	0.00
Rear1	-682.10	398.81	0.087
Rear2	1728.32	437.71	0.000
Rear3	2793.32	1188.62	0.019
2WD	-3761.50	915.73	0.000
Rep_Sal	-4661.08	851.67	0.000
Constant	15229.17	2893.00	0.000

[1] Robust standard errors calculated to correct for heteroskedasticity of the error term.
Adjusted R-squared = 0.7498
RMSE = 5430.1
n = 1,100

Nate reflected on his new results.

> "*The signs of all variables fit my original hypotheses. All variables are significant at the 5 percent level other than* ***hp***, ***hp²***, ***Auto***, ***Air_Heat***, *and* ***Rear1***, *and a couple of those variables are very close to significant (especially* ***hp*** *with a p value of 0.055), and all possess signs and magnitudes that would coincide with theory*."

He then considered the goodness of fit and predictive accuracy.

> "*The adjusted R-squared improved marginally from my original model as well as my RMSE. Since the RMSE represents the square root of the variance of my residuals, it has the useful property of being in the same unit as my dependent variable (price) and gives me an idea of how closely predictions using my model would be expected to match actual values*."

Nate evaluated the magnitude of the coefficients estimated and performed a mental interpretation for a few of them.

> "*For any variable not included as a squared term, I can interpret the coefficient itself as the variable's marginal effect. This is because a marginal effect of any variable can be calculated as the partial derivative of the price equation with respect to that variable. This suggests that for a variable included as both a linear and squared term the marginal effect is not constant. If I take, for example, the partial derivative of the price equation with respect to* ***hp****, I find its marginal effect to be equal to* **172.3 + 2.4 *hp***."

Nate took mental note that this suggests that the marginal effects of variables included as squared terms depend on the level of the variable themselves.

> "*For variables included only linearly, the marginal effects are constant. The coefficient for Year of 2,650 suggests that holding all other variables constant, used tractor prices have been increasing by $2,650 each year over the years 2020–2022. Todd will be keen to see this result as it addresses his third objective concerning inflation of used tractor prices*," Nate thought.

> "*A coefficient of -510 for* ***Age*** *suggests that while holding all other variables constant, for each additional year in age of a tractor, its value would be expected to decrease on average by $510. All my "Make" variables included are relative to the reference make of John Deere. Since the coefficients for the other makes are all negative and statistically significant, I can conclude that I would expect all other makes to be discounted relative to a John Deere tractor by the value of their coefficient holding all other variables constant. This should help to address Todd's second objective. Switching my* ***R_Hyd*** *variable to discrete dummy variables was a good idea. I can now get an idea of the marginal differences between various quantities of remotes. It appears that based on the lack of statistical significance for Rear1, buyers don't really value having only one rear remote as compared to none. However, increasing to two rear remotes suggests the tractor value would increase by $1,728 with another $1,065 added to those tractors that have three or more rear remotes. These marginal values are exactly what Todd is looking for and should work great to begin helping us set our prices on our used tractors*."

3.8 Making Predictions

Nate wanted to test the model to be sure he felt it could make reasonable predictions of price to accomplish Todd's first objective. Nate called one of the local dealerships and spoke with the manager. He asked the manager to provide him with an example of a tractor recently taken in on trade that had been sold. The manager told him they had just sold a 2017 Massey Ferguson 60 horsepower tractor last week for $32,000. It had 250 hours on it, was an automatic transmission, came equipped with two rear remote hydraulics, and included a cab. Nate quickly input the tractor's information into a spreadsheet and then using the marginal values of the attributes calculated with his hedonic regression equation, he estimated the tractor value (as in Table 6) to be $37,153. Nate thought the prediction was reasonable and suggested to him that the dealership had undervalued the tractor by about $5,000. Of course this was only one observation, and given the RMSE of the model was approximately $5,500, Nate felt the manager was not too far off with his pricing. Nate felt the next steps were to collect additional samples from other dealerships across the country and evaluate the performance of the model using out-of-sample data. After that, the only thing left to do was write up his results into a report that he could provide to Todd and the management team.

Table 6. Used Tractor Price Prediction Example

Variable	Coefficient	Attributes	Marginal Values
Year	2650.51	3	$7,952
Age	-510.36	5	-$2,552
Age^2	172.30	60	$10,338
hp	1.20	3600	$4,320
hp^2	-5.30	250	-$1,325
Hours	0.0004	62500	$25
MAKES			
Case IH	-2103.92	0	$0
Kubota	-3071.34	0	$0
Mahindra	-10405.18	0	$0
Massey Ferguson	-6086.24	1	-$6,086
New Holland	-4316.69	0	$0
Auto	710.31	1	$710
Air_Heat	766.89	0	$0
Cab	6813.91	1	$6,814
Rear1	-682.10	0	$0
Rear2	1728.32	1	$1,728
Rear3	2793.32	0	$0
2WD	-3761.50	0	$0
Rep_Sal	-4661.08	0	$0
Constant	15229.17	1	$15,229
		Total Expected Value	**$37,153**

About the Authors: Ryan Feuz is an Assistant Professor at Utah State University (Corresponding author: ryan.feuz@usu.edu).

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