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Research

Job Attribute Preferences of Undergraduate Agricultural Majors—Do They Match with Careers in Grain Merchandising?

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Abstract
The purpose of this study is to gain a better understanding of student job attribute preferences for grain merchandising careers. Undergraduate students in the College of Agriculture at Fort Hays State University and Kansas State University responded to a choice-based conjoint survey that captures students' expectations about grain merchandising careers. Parameter estimates from a conditional alternative specific constants logit model are used to estimate willingness to accept changes in salary for preferred job attributes. Results suggest that students have strong preferences for working in rural locations and working at smaller companies and have professional growth opportunities. The students exhibited less of a preference for frequent performance feedback and oral communication, and a focus on risk management and analysis. These results should inform faculty advisors of the important attributes of grain merchandising and help agribusinesses to improve employee recruitment techniques and employee retention.

1 Introduction

Of the many career alternatives available for students enrolled in agricultural economic undergraduate programs, some will pursue careers in the merchandising of agricultural commodities. A grain merchandiser manages commodity price risk; executes futures, options, spot, and forward contracts; and arranges transportation and storage. Although students can learn the underlying structures and functions of grain merchandising from college, most training is on the job. Thus, with little or no practical experience, an undergraduate student rarely understands this career path. Additionally, employers including agricultural cooperatives, grain processing, and food companies have full knowledge of grain merchandising, but know less about the aspects of the job that undergraduate students may find appealing. Thus, employers and potential job candidates have incomplete information about one another. The differences between the employers and job candidates provides an opportunity to learn what is important to the employer and which workplace and social trade-offs students are willing to make to work as grain merchandisers.

This labor study focuses on better understanding student job attribute preferences for grain merchandising careers. Insights from this study also provide guidance for advisors who are helping students pursue this career path. The primary research question for this study was: how well do student job attribute preferences match with a career in grain merchandising? Support for this research question was found generally in the academic literature and specifically among practitioners interested in recruiting, selecting, and retaining grain merchandising employees (Marchant and Zepeda 1995; Wachenheim and Lesch 2004; McGraw et al. 2012). Employers look for the hard skills of futures market risk management, as well as soft skills to communicate with clientele, solve day-to-day organizational problems, and discern from a variety of market information sources (Kliethermes, Parcell, and Franken

2011). The findings of this study could inform students of companies' recruitment processes and advance the advisor/advisee discussion of alternative career opportunities.

A literature review revealed multiple theoretical perspectives on the development of employees, particularly among human capital theory, transaction cost theory, and resource-based view (RBV) theories of the firm. Common to each theory is the theme of an intentional approach to individual choices and to long-term human resource development by an organization. Human capital theory links investment in the organization's key asset—employees—to increased productivity through the development of knowledge, skills, and ability in order to sustain a competitive advantage (Becker 1962; Schultz 1970; Smith 1998). Transaction cost theory examines why firms organize internally what might otherwise be conducted in the marketplace (Coase 1937). According to this theory, transaction-specific assets can also be human in nature, in the form of asset specificity of knowledge or skill (Anderson 1985).

As with other types of special purpose assets, transaction-specific human assets represent a source of value unique to a particular firm. This is consistent with RBV theories of the firm. The focus of RBV theories is on an organization retaining and developing human resources that are valuable, rare, and difficult to imitate, further enhancing the organization's competitive advantage (Penrose 1959; Barney 1991; Walton and Gupta 1999; Garavan et al. 2001). Studies on human capital, transaction costs, and RBV suggest that human resources are a source of competitive advantage for any organization. The three theories generally converge to determine both employee and firm-level outcomes. Although a review of each of these frameworks is beyond the scope of this study, it has been long and widely asserted that employees are the preeminent organizational resource and key to achieving outstanding performance.

To more fully understand students' preferences for careers as grain merchandisers, a survey using a choice-based conjoint experiment was designed to capture students' expectations about grain merchandising careers. Students' preferences for grain merchandising job attributes were estimated using a conditional alternative specific constants logit model, and parameter estimates were used to estimate willingness to accept (WTA) changes in salary for preferred job attributes. The attributes considered in this study were as follows: firm size, performance feedback, work location, professional growth opportunities, risk management analysis, risk preferences of the company, behavior preferences of the company, and salary. Few empirical research studies have been conducted on the expectations of the employer and employee for grain merchandisers. The study closely resembles duties of grain merchandisers, and the conjoint experiment helps to elicit responses from respondents concerning preferences for those duties. Therefore, the results of this study should benefit employers and help them recruit new employees.

Results from the conjoint survey suggested that rural grain-marketing agribusinesses offered job attributes that were appealing to many students. Students that responded to the survey had strong preferences for working in rural locations and for working at smaller companies. Furthermore, the students preferred to work for companies that afforded them the opportunity for professional growth. These findings should assist rural agribusinesses in recruiting and retaining the best grain merchandising talent to maintain their human capital comparative and competitive advantages. Furthermore, these results provide faculty advisors the key attributes of a grain merchandising job. A set of questions was created to provide advisors with a method of identifying advisees who might show an interest in a grain merchandising career.

2 Methods to Assess Preferences for a Grain Merchandising Job

Agribusinesses hiring employees with the ability to perform specific tasks is important, but the employee's abilities in other general areas, such as technical and communication skills, are also important to firms' success (Wachenheim and Lesch 2004; Ibnu et al. 2015; Meyerding 2018). In this study, a choice-based conjoint analysis was used whereby students selected the most appealing grain merchandising jobs that had varying specific and general attribute levels. Results from this choice experiment should inform faculty advisors of the important attributes of grain merchandising and help agribusinesses to improve employee recruitment techniques and employee retention.

Conjoint analysis is an established approach for understanding attribute trade-offs and choices in marketing research (Gracia, Loureiro, and Nayga 2009) and is consistent with random utility theory (McFadden 1974). Choice experiments assume that the utility of a good can be derived from different product attributes, that participants' choices are rational, that participants seek to maximize utility subject to innate stable preferences, and that participants have perfect discrimination capabilities (Lancaster 1966; Lancsar and Savage 2004).

To assess student preferences, this study used a conjoint survey to uncover the attributes that appealed to the students relative to the organizational, social/behavioral, and technical aspects of a grain merchandising job. Regression techniques were employed to model students' choices as a function of the attributes of the grain merchandising job. The students' choices, over several alternatives, were analyzed to deduce the relative importance of these attributes. When the students were forced to make difficult trade-offs, what they truly valued could be determined (Boyer, Briggeman, and Norwood 2009). The significance and magnitude of regression coefficients indicate the relative importance of the attributes that influenced the respondents' choices. Estimates provide insight into the value that students place on each aspect of the job and allow inferences to be drawn from various grain merchandising job scenarios.

2.1 Survey Construction

The examined job attributes previously mentioned were used to determine students' interests in a grain merchandising career. To evaluate respondents' preferences for job attributes inherent to companies that employ grain merchandisers, the survey questions were developed with input from merchandising practitioners. The attributes used in the conjoint analysis were developed from a series of industry meetings and investigations from reviewing job descriptions and from having discussions with early-career and seasoned grain merchandisers employed in multinational grain companies and farmer cooperatives. The technical or professional attributes included the extent to which the respondent valued the merchandising skills required by the firm and the respondents' disposition toward acquiring these skills (Kliethermes et al. 2011). The attributes and attribute levels used in the conjoint analysis are listed in table 1.

The first attribute, company size, focused on the number of employees, ranging from small (less than 50), to medium (between 50 and 250), to large (greater than 250 employees) sized companies. Barber et al. (1999) found that the size of the company was a significant factor for individuals in the job market. The second merchandising attribute, performance feedback, was particularly important and examines if new employees prefer autonomy, accountability, and less frequent feedback on the job. The students were asked to choose between weekly (more frequent) or monthly (less frequent) interactions with a supervisor. The third attribute was work location. One characteristic that is especially important for agricultural students is the location of the company. Marchant and Zepeda (1995) and McGraw et al. (2012) found that agricultural students had a strong preference for working in a rural location.

The fourth attribute, professional growth opportunities, was included to measure students' preference for future job promotions and professional development prospects. For instance, "Yes" indicates the job offer's professional growth opportunities. A "None" option indicates there is no opportunity for professional growth. The fifth attribute, oral communication, examined students' penchant for communicating in person or by telephone compared with a preference for other information and communication technologies such as text messaging or email. The "Yes" attribute level for oral communication indicates oral communication is required and "No" for no required oral communication. Risk management and analysis is the sixth attribute and is a task often used by grain merchandisers. The attribute was explained as an "interest in understanding future and option markets." The "Yes" or "No" attribute levels for risk management analysis indicate whether respondents prefer job duties that include dealing with risk management tasks, such as futures markets, basis, and hedging.

Table 1. List of Attributes and Attribute Levels for Grain Merchandising Job Choice Tasks

Attributes of Merchandising	Attributes Levels
1. Company Size	Small, Medium, Large
2. Performance Feedback	Weekly, Monthly
3. Work Location	Micropolitan (Rural) Area, Metropolitan (Large City) Area
4. Professional Growth Opportunities	Yes, None
5. Oral Communication	Yes, No
6. Risk Management and Analysis	Yes, No
7. Behavior Preference	Assertive, Appeasing
8. Risk Preference	Risk Neutral, Risk Taker
9. Salary	\$35,000; \$45,000; \$50,000; \$55,000; \$60,000

The seventh attribute was behavior preference. Consultations with various companies revealed that each company tended to have one of two cultures. These cultures represented two behavioral attribute levels: "assertive" and "appeasing." Assertive behavior is described as the confidence to make and defend a decision, while appeasing behavior is described as acceding a decision to an ongoing trading partner to avoid conflict or end a disagreement.

The eighth attribute was risk preference. When faced with this attribute, students were encouraged to consider their attitudes toward risks. Risk is a key factor in decision-making behavior. Attribute levels of risk-taking and risk-neutral behavior reflected students' risk preference and conveyed whether a student preferred an employer who pursued riskier or safer trading decisions to buy, sell, or store grain. For instance, a student might view an employer's penchant for more rules and procedures as a way for managers to intervene, which minimizes the risky behavior in the organization. The final attribute was the starting annual salary. The attribute levels of \$35,000, \$45,000, \$50,000, \$55,000, and \$60,000 reflect a range similar to the paid compensation for new grain merchandisers.

A fractional experimental design was used to construct choice tasks to elicit preferences among combinations of job attribute levels. The attribute levels, shown in table 1, could be combined into a full factorial design of 1,920 = ($2^7 \times 3 \times 5$) possible choice profile configurations, which was too large for practical use. Thus, Sawtooth Software (Version 8.4.5, Orem, UT) was used to create the survey design. Johnson et al. (2013) report that the balanced-overlap method used by Sawtooth Software identifies a randomized design that ensures a well-balanced and orthogonal fraction of the full factorial design. The software designs a large set of choice tasks (3,600 tasks for this experiment from the full factorial) and then randomly selects from this set of choice tasks to form unique blocks (for each respondent) that maintains orthogonality and maximizes design efficiency. The design consisted of twelve choice tasks (per block) for each respondent. Within each choice task, students chose among three options: merchandiser job A, merchandiser job B, or the opt-out or "None" option. Within each job choice, combinations of nine attributes and their levels the software used to design the experiment allows for orthogonality to be maintained and the identification of all main and potential interaction effects (Kuhfeld, Tobias, and Garratt 1994). Figure 1 shows a sample choice task completed by student respondents.

<table>
<tr><th>Attribute</th><th>Job A Opportunity</th><th>Job B Opportunity</th><th>Job C Opportunity</th></tr>
<tr><td>Company Size</td><td>Less Than 50</td><td>More Than 250</td><td rowspan="9">Neither Job “A” or “B” is appealing.</td></tr>
<tr><td>Performance Feedback</td><td>Yes</td><td>No</td></tr>
<tr><td>Work Location</td><td>Rural Area</td><td>Large Metropolitan</td></tr>
<tr><td>Professional Growth Opportunities</td><td>None</td><td>Yes</td></tr>
<tr><td>Oral Communication</td><td>Yes</td><td>No</td></tr>
<tr><td>Risk Management and Analysis</td><td>Yes</td><td>No</td></tr>
<tr><td>Behavior Preference</td><td>Assertive</td><td>Pleasing</td></tr>
<tr><td>Risk Preference</td><td>Yes</td><td>No</td></tr>
<tr><td>Starting Annual Salary</td><td>$45K</td><td>$50K</td></tr>
<tr><td>Please Select the Most Preferred Opportunity</td><td>Select</td><td>Select</td><td>Select</td></tr>
</table>

Figure 1: Sample Choice-Based Conjoint Grain Merchandising Job Choice Task

The survey began with a definition of grain merchandisers as follows: “agribusiness firms involved in the procurement, handling, storing, and re-distribution and processing of grain. These firms include country grain elevators, cooperatives and noncooperatives, shippers and exporters, processors, and feeders.” Each grain merchandising employment opportunity was presented as being advertised by an agribusiness firm that was reputable, financially stable, and positioned for future growth.

The survey used questions related to relationships that best demonstrated how the student was influenced by their social environment. The questions also aimed to identify which characteristics were universal across the sample of students. The questions included descriptions of the students’ academic institutions, their coursework, the people who influenced their decisions, their hometown, and their preference for work location.

2.2 Survey and Data

Undergraduate students majoring in agricultural economics or agribusiness management from Fort Hays State University and Kansas State University were sampled for this study. These universities were selected based on their agricultural and natural resource programs, as well as their willingness to share student email addresses. Furthermore, these two universities provided a unique sample of student populations. Fort Hays State University’s agricultural student enrollment in 2018 was 386, which was considerably smaller than Kansas State University’s 2018 agricultural student enrollment of 2,512. Even though there is a notable size difference, the agricultural students at each university follow a similar curriculum. Although having additional universities in the data might improve the representativeness of the data, being able to compare and contrast these two related, yet different universities could provide unique insights into student perceptions of a grain merchandising career.

All students received an email cover letter describing the intentions of the survey and an email containing a link that led them to the choice survey. The first reminder was emailed five days after the initial communication, and a second reminder notification was sent two days later. To further increase the response rate, all survey respondents were entered into a drawing to win one of three $100 Visa gift cards.

A total of 170 students completed the survey. To arrive at a sample of usable responses, the following respondents were eliminated: (1) inconsistent respondents; (2) survey time outliers or respondents who spent less than 1 minute taking the survey (which was 2 standard deviations below the average survey time of 11 minutes; support for removing these outliers was found in Greszki, Meyer, and Schoen [2015])[1]; and (3) missing value responses. A total number of 153 usable responses remained, which resulted in a 30.1 percent response rate.

Table 2: Descriptive Statistics of Respondents

Variable	N	Frequency
Class Rank:		
Freshman	153	0.07
Sophomore	153	0.11
Junior	153	0.37
Senior	153	0.45
Gender:		
Male	153	0.64
Female	153	0.36
I was raised in a:		
Rural Location	153	0.89
Urban Location	153	0.11
How would you describe your academic institution?		
Junior College	153	0.01
Smaller to Midsized University	153	0.40
Larger University	153	0.59

Descriptive statistics for the sample are reported in table 2. The respondents had a higher representation of third-year and fourth-year students. Junior and seniors made up 82 percent of the sample, while freshmen and sophomores comprised the remaining 18 percent. Nearly 65 percent of the respondents were male, and the vast majority (89 percent) of those who responded to the survey grew up in a small rural town. About 60 percent of the sample attended the larger university (Kansas State University), while 40 percent of the respondents attended the smaller university (Fort Hays State University).

[1] The response behavior of individual respondents varies considerably during a survey. For each respondent to the web survey, we are able see the amount of time each respondent spent on each task. According to Greszki et al. (2015), too fast responses, in web surveys indicate low data quality, and evidence indicates that removing “too fast” responses does not alter marginal distributions. The impact on the explanatory models yield negligible coefficient differences.

A set of questions was presented to the students to assess their interests in the career field and type of organization and their preference for a merchandising career across various agricultural commodities. company, whereas 30 percent did not prefer the type of firm that was engaged in grain merchandising (table 3). Of the respondents, 78 percent identified a medium to high interest in a grain merchandising career path. The respondents also chose a commodity they would prefer to focus on for their career. The vast majority of students preferred to work with grains and livestock, while very few students preferred to work with dairy, energy, or transportation.

Table 3: Descriptive Statistics of Respondents Willing to Pursue a Career in Merchandising

Variable	N	Frequency
How would you describe your interest in pursuing a career in grain merchandising?		
Low	153	0.22
Medium	153	0.54
High	153	0.24
I'd prefer to start a career in merchandising:		
Cooperative	153	0.30
A Grain Company (Not a Cooperative)	153	0.21
A Food Company	153	0.03
A Trading Company	153	0.16
It Does Not Matter	153	0.30
Commodity Preferences for Work Focus (Select All That Apply)		
Grain (Wheat, Soybeans, Corn, Rice)	153	0.34
Live Animals/Animal Proteins (Cattle, Swine, Poultry)	153	0.27
Dairy (Milk, Cheese, Butter)	153	0.05
Feed Ingredients (DDGs, Wheat Midds, Soybean Meal, etc.)	153	0.16
Energy (Gas, Electricity, Oil)	153	0.09
Freight (Trucks, Rail Barge)	153	0.09

2.3 Empirical Model

To conceptualize the j^{th} student's decision to pursue the i^{th} job that fit his or her employment expectations, an indirect utility function was assumed of the form: $U_{ij} = V_{ij} + \varepsilon_{ij}$, where U_{ij} is the unobservable utility that student *j* associates with job choice *i*; V_{ij} is the systematic (explainable) component of the utility individual *j* associates with alternative *i*; and ε_{ij} is the random (unexplained) component associated with individual *j* and choice *i*. The study assumed individual students would choose the i^{th} alternative if the utility derived from that alternative was greater than the utility derived from any other alternatives in a choice set.

The systematic component of utility was assumed to be linearly additive of the form:

$$V_{ij} = \alpha_j + \beta_1 Large_{ij} + \beta_2 Feedback_{ij} + \beta_3 Rural_{ij} + \beta_4 ProfGrowth_{ij} + \beta_5 Behavior_{ij} + \beta_6 RiskTaker_{ij} + \beta_7 RiskAnalysis_{ij} + \beta_8 OralComm_{ij} + \beta_9 Salary_{ij} + \varepsilon_{ij} \quad (1)$$

The coefficients, β_n, n = 1, … 9, represent the marginal utilities of the job attributes associated with grain merchandising, as described in table 1. Alternative specific constants (α_i) were included in equation (1) to capture preferences for those students that may have preferred any available grain merchandising job option and also to capture preferences for those that did not prefer a grain merchandising job (the opt-out option). Most of the attributes were binary and were incorporated as dummy variables, with "1" indicating the presence of a job attribute and "0" indicating otherwise. To help with the ease of interpretation, company size, *Large*, was entered into the model as "1" indicating a large company and "0" otherwise.[2] The remaining binary variables in equation (1) are now described relative to the presence of the attribute or the binary variable equals "1." *Feedback* indicates frequent performance feedback. *Rural* is for a rural work location. *ProfGrowth* means the job offers professional growth opportunities. *Behavior* indicates the job requires an assertive behavior. *RiskTaker* refers to a job that prefers a risk-taking preference. *RiskAnalysis* means the job requires risk management analysis. *OralComm* indicates oral communication is a requirement in the job. *Salary* refers to entry-level remuneration. Finally, assuming ε_i was distributed mean zero extreme value Type 1, an alternative specific constant conditional logit model was estimated where the base alternative was the option of neither grain merchandising job being selected (i.e., an opt-out option).

Coefficient estimates in the model capture students' preferences. As such, the present study was a labor supply study as opposed to a demand side study. Therefore, the expectation was that the sign of β_9 on *Salary* would be positive. To estimate WTA or students' marginal willingness to substitute initial salary for preferred job attributes, the estimated β of a given job attribute was divided by the absolute value of β_9, the coefficient on initial starting salary (Ryan, Gerard, and Amaya-Amaya 2008). For example, assume the parameter estimate on *Large* was positive. That would yield a positive WTA measure, which would be interpreted as the student is willing to forgo $X of salary to work for a larger company. If the *Large* parameter estimate was negative, then the negative WTA measure would be interpreted as the student would need to receive $X additional salary to work for a larger company. Interpretation of the significance of job attributes focuses students' WTA or acceptance of salary trade-offs that enables them to receive preferred job attributes.

The average WTA for all data is insightful but gaining additional insights from a subsample helps to capture how respondents differ on the appealing aspects of the job. The first subsample are those students who have a high interest in a grain merchandising career versus those who do not have a high interest. The second subsample are those students who attend a large university versus those who attend a smaller university. Estimating WTA for these subsamples illustrates the heterogeneity in preferences across students. These differences could affect how we understand their interests in the career path.

3 Results

Conditional alternative specific constant logit models were estimated to identify the most highly preferred grain merchandising job attributes. To examine the heterogeneity of the students' preferences, separate conditional logit models were estimated on various subsamples of the data as well. Estimating separate models allowed for straightforward comparisons of the various parameter estimates for each subsample.[3] Table 4 presents the results for the base model, which suggests a high interest in working as a grain

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[2] Conditional logit models were estimated using the other dummy variables as Large = 1, Medium = 1, and 0 otherwise as well as Large = 1, Small = 1, and 0 otherwise. In each instance, Large was the only statistically significant variable among these dummy variable combinations.

[3] Given the data were collected via a conjoint survey, and according to Hoffman and Duncan (1988), a conditional logit model is estimated because it is preferred over a multinomial logit. To account for the differences across student characteristics, a full conditional logit model with interaction effects could be estimated. However, estimating separate conditional logit models for each subsample of data results in the same model findings as the full conditional logit model. Furthermore, the separate model approach allows for easy comparisons of the parameter estimates across subsamples.

Table 4: Alternative Specific Constant (ASC) Conditional Logit Estimation Results for Grain Merchandiser Job Attributes

	Base Model (Full Sample)		High Job Interest (Subsample)		Lower Job Interest (Subsample)		Large University (Subsample)		Small University (Subsample)	
Job Attribute Variables	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.
Larger Company Size	-0.20*	0.04	-0.22*	0.08	-0.19*	0.05	-0.21*	0.06	-0.17*	0.07
More Frequent Performance Feedback	0.12	0.06	0.01	0.12	0.15	0.08	0.05	0.08	0.21*	0.10
Rural Work Location	1.13*	0.07	0.41*	0.13	1.40*	0.08	1.09*	0.09	1.21*	0.11
Professional Growth Opportunities	0.43*	0.06	0.34*	0.13	0.50*	0.08	0.47*	0.08	0.38*	0.10
Assertive Behavior Preference	0.04	0.06	-0.14	0.13	0.07	0.08	0.08	0.08	-0.04	0.10
Risk Taker Preference	-0.16*	0.06	-0.11	0.13	-0.17*	0.08	-0.28*	0.08	0.01	0.10
Risk Management Analysis Is in the Job	0.08	0.06	0.20	0.13	0.02	0.08	0.09	0.08	0.06	0.10
Oral Communication Required	0.11	0.06	0.07	0.12	0.12	0.08	0.14	0.08	0.06	0.11
Salary ($1,000)	0.07*	0.004	0.08*	0.009	0.07*	0.005	0.07*	0.006	0.07*	0.007
ASC Job 1	1.79*	0.15	2.21*	0.30	1.67*	0.18	2.01*	0.21	1.51*	0.24
ASC Job 2	1.78*	0.16	2.33*	0.30	1.61*	0.18	1.99*	0.21	1.49*	0.24
log L (0)	-1,455.45		-387.20		-1,040.60		-846.49		-603.25	
log L (max)	-1,417.43		-381.04		-1,008.47		-824.74		-586.55	
Wald χ^2 statistic	427.91		86.35		363.71		254.18		175.49	
Number of observations	5,508		4,140		1,368		2,232		3,276	
Number of student respondents	153		115		38		62		91	

Note: Each set of parameter estimates, and standard errors are tied to a particular data set. Base model is the full data; high job interest indicates that the student has (=1) or does not have (=0) a high interest in a grain merchandising job; large university indicates the student stated that they attend (=1) or do not attend (=0) a large university.
* Indicates statistical significance at the 5 percent level.

merchandiser, irrespective of the size of the students' university. Table 5 shows calculations concerning the salary a student would be willing to accept or forgo for a particular job attribute level.

3.1 Base Model (Full Sample of Respondents)

The results of the base model (table 1) suggested that agricultural students preferred to work in rural areas. The average WTA to accept a lower salary to work in a rural location was $16,143. Part of this preference was likely tied to a lower cost of living in a rural location compared with an urban location. This result could be tied to a preference for a rural lifestyle. Identifying the exact reason was not within the scope of this study. Regardless, of all of the job attributes shown to the students, the highest WTA was for the ability to live and work in a rural area.

Students showed a strong preference for an employer that offered professional growth opportunities. On average, the survey sample was willing to choose jobs that paid $6,143 less in salary if the company provided opportunities to further their career. Presumably, students were anticipating that, if the company enhanced their job skills, this would open future possibilities for promotions or other ways to make up the forgone salary.

In the base model, students did not prefer two of the job attributes: companies larger in size and companies with a perceived higher risk-taking work environment. In each case, an increase in the average annual salary that students had to receive to prefer these jobs was about $3,000.

3.2 Subsample Results for Respondents by Level of Job Interest

The data provided additional insight about students' interest levels in working as grain merchandisers. The differences between having interest for the job or not a priori provided some insight into students' motivations to pursue this career path. The most striking difference between those with a high interest and those without was in preference for work location. Both groups of students preferred to work in a rural location and were willing to accept a lower salary to work there. However, those with a strong interest in working as grain merchandisers were only willing to forgo an average of $5,125 in salary to work in a rural location. Those without interest were willing to forgo $20,000 in salary. Furthermore, the 95 percent confidence intervals of these two WTA measures are statistically different from each other. Potentially, if the preference to live in a rural location is strong enough, it might be possible for rural employers to recruit students who do not have an interest in a grain merchandising career. Of course, more research is necessary to understand the motives of students who do not have a high interest in a particular career but have a strong preference to live in a rural area.

The preference estimate was significant and positive for professional growth opportunities among respondents with interest in the career. Students were willing to accept $4,250 less in salary if professional growth opportunities were available. The subsample model parameter estimates were statistically significant and negative for company size and the risk-taking attribute. In the subsample, students did not prefer working for larger companies with a preference for taking risks. A prospective employer would have to compensate for these less desirable job attributes by offering $2,750 more in annual salary for students to work in a larger company and $1,375 for students to work for a risk-taking company.

3.3 Subsample Results for Respondents by University Size

Agricultural students with preferences to work for a small company, in a rural work location, with professional opportunities, and with fewer risk-taking activities were consistent for students attending larger and smaller universities. Some significant differences did emerge. The WTA estimates in table 5 suggest that students from a smaller university had a stronger preference to live in a rural area compared with students attending a larger university. Students at the larger university would accept a salary of $6,714 less to work for a company with professional growth opportunities, whereas students at the smaller university were willing to accept $5,429 less if professional growth opportunities were available on the job.

Table 5. Salary Trade-off Estimates for Grain Merchandising Job Attributes

Job Attribute Variables	Base Model (Full Sample)	High Job Interest (Subsample)	Low Job Interest (Subsample)	Large University (Subsample)	Small University (Subsample)
Larger Company Size	-$2,857	-$2,750	-$2,714	-$3,000	-$2,429
	[-$4,083, -$1,606]	[-$4,956, -$696]	[-$4,208, -$1,263]	[-$4,697, -$1,462]	[-$4,357, -$535]
More Frequent Performance Feedback	$1,714	$125	$2,143	$714	$3,000
	[-$75, $3,530]	[-$2,873, $3,236]	[-$27, $4,300]	[-$1,631, $3,032]	[$229, $5,891]
Rural Work Location	$16,143	$5,125	$20,000	$15,571	$17,286
	[$13,826, $18,699]	[$2,035, $8,448]	[$16,948, $23,429]	[$12,414, $18,574]	[$13,326, $21,220]
Professional Growth Opportunities	$6,143	$4,250	$7,143	$6,714	$5,429
	[$4,268, $8,100]	[$1,081, $7,485]	[$4,805, $9,455]	[$4,238, $9,186]	[$2,360, $8,383]
Assertive Behavior Preference	$571	-$1,750	$1,000	$1,143	-$571
	[-$1,238, $2,368]	[-$4,883, $1,372]	[-$1,120, $3,180]	[-$1,150, $3,502]	[-$3,373, $2,324]
Risk Taker Preference	-$2,286	-$1,375	-$2,429	-$4,000	$143
	[-$4,161, -$500]	[-$4,608, $1,669]	[-$4,655, -$282]	[-$6,407, -$1,582]	[-$2,793, $2,885]
Risk Management Analysis Is in the Job	$1,143	$2,500	$286	$1,286	$857
	[-$725, $2,913]	[-$616, $5,693]	[-$1,832, $3,895]	[-$1,012, $3,676]	[-$2,065, $3,660]
Oral Communication Required	$1,571	$875	$1,714	$2,000	$857
	[-$276, $3,361]	[-$2,172, $3,979]	[-$472, $3,895]	[-$342, $4,359]	[-$2,066, $3,637]

Note: Estimates are calculated by taking a job attribute variable parameter estimate from table 4 and dividing it by the salary parameter estimate. Then, this ratio is multiplied by $1,000 because the salary parameter estimate is show in $1,000s. Number in brackets are the 95% confidence interval estimated using the Delta method.

Additional differences were identified between students at each university. Students at a smaller university had a stronger and statistically significant preference for more frequent performance feedback. These students were willing to accept a $3,000 lower salary, whereas their larger university student counterparts had a statistically insignificant estimate of $714. Students at a larger university exhibited a strong preference to work for a company that did not have a risk-taking preference. These students would require an additional $4,000 of salary to accept that position, whereas their smaller university student counterparts had an estimate nearly equal to $0.

It appears there are differences between the agricultural student populations at these two universities. Potentially the student motivations for attending a smaller or larger university play a role in this estimated WTA salary differences. Possibly there are other reasons. More research is necessary to identify why these differences exist.

3.4 Job Attribute Preference Rankings

Finally, part-worth utilities were examined to identify which job attributes were most preferred by student respondents. Using the alternative specific constant model parameter estimates, the part-worth utilities were calculated for each attribute level. The relative importance scores were then calculated so that all scores summed to 100 percent. Therefore, if each attribute was considered equally important, each relative importance score for the nine attributes would approximately equal 11 percent.

Table 6 shows the average relative importance scores for each attribute and ranks them based on order of preference. The most preferred attribute was salary, with a relative importance score of 37.6 percent. Next was rural work location at 31.1 percent, followed by available professional growth opportunities at 12.3 percent. All other attributes and levels were not as important to the students, which suggest students may not have been aware of each attribute's importance to grain merchandising, or students were not aware of the day-to-day aspects of communication, risk management, assertive behavior, and frequent performance feedback.

4 Conclusions and Recommendations

Employee selection is important for a company's success, and poor recruitment practices can result in financial losses. For example, if a candidate's competency is not accurately assessed, the candidate may make mistakes that can hinder productivity. If a new employee needs to be retrained or replaced, this takes up more company time that could otherwise be invested toward advancing other employees.

The purpose of this study is to help employers better understand students' desires about grain merchandising jobs. The results showed that students preferred a job in a rural location and provided professional growth opportunities. The students exhibited less of a preference for frequent performance feedback, oral communication, and a focus on risk management and analysis. Results showed that students valued the more nontechnical aspects of grain merchandising positions. In fact, many industry professionals have stated that grain merchandising is largely a relationship business (Kliethermes et al. 2011).

Heterogeneity within the student sample did yield some differences. Student preferences for a lower salary varied considerably across interest level in the profession and across university size. This suggested that students placed differing values on professional growth opportunities, prospects for high future earnings, and work location. Large and meaningful differences between attributes should help clarify and direct a talent management strategy. This study found that respondents agreed that salary and work location were the most important factors in choosing a career in merchandising. The findings also suggested that nonfinancial attributes influenced students' interests in pursuing prospects with a small company with professional growth opportunities.

The nonfinancial aspects of job choice tended to be firm-specific, suggesting that employer's recruitment plans should involve these attributes in a manner that is attractive to potential employees. Results suggested that a focused effort is needed to emphasize the attractiveness of the position through

Table 6: Relative Importance of Grain Merchandising Job Attributes

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9
Job Attribute	Salary	Work Location	Professional Growth Opportunities	Risk Preference	Company Size	Performance Feedback	Oral Communication	Risk Management Analysis	Behavior Preference
Preference Ranking	37.6%	31.1%	12.3%	4.7%	4.0%	3.6%	3.2%	2.3%	1.2%

Note: Preference rankings were calculated using the relative importance of attribute part-worth utilities for each student respondent and then calculating the average.

its job attributes. Employers should emphasize the opportunities available to new grain merchandisers within the company and describe the career paths of some of the recent hires.

Employers should be mindful of how to help new employees develop a greater comprehension for the least preferred job attributes. For instance, employers could make hard-skill training opportunities available to reinforce the importance of risk management and analysis. Or, employers could provide soft-skill development opportunities that reinforce assertiveness, which is needed to defend commodity trading decisions made under uncertain market conditions.

Not only should companies take advantage of these results, but knowing the job attributes should also help academic advisors lead a student who exhibits these preferences toward a career in grain merchandising. Academic advisors should present career options that cause the student to think carefully about their goals. For example, the student's attention could be drawn to the attributes that are related to grain merchandising and often evaluated by employers. Instruction must include not only the technical aspects of the career field but the unique professional and social aspects of grain merchandising, as well.

Similar to Howe and Strauss (2000), an academic advisor could use these results to impress upon their advisees the importance of technical and more general skills. However, some deficit areas may exist among advisees that could hinder their ability to reach their career goals. Although identifying these deficit areas is beyond the scope of this paper, it is well within the objective of the paper to pose some questions an advisor could ask to help start and even lead the conversation with an advisee. Here are a set of questions based on the research that an academic advisor could use:

1. What are your strengths and weaknesses, and how well do they match up with the job attributes of grain merchandising?
2. What concepts or ideas do you want to know more about?
3. How desirable is it for you to live in a rural location?
4. As a follow-up to the previous question, have you considered a career in merchandising?
5. If money were not an issue, would you like to be a grain merchandiser for five years after graduation?
6. How desirable are professional growth opportunities in a career?

Guiding students to find answers to these difficult questions will help them align their ambitions and set realistic expectations. Faculty advisors can assist in the development of a career mind-set that is resilient and a career trajectory that can adapt to changes and take advantage of unplanned as well as sought-after opportunities. In short, faculty and those in the industry should use these results to better understand students' preferences for aspects in a grain merchandising career.

This study has some limitations. The sample included only students in colleges of agriculture. Since early-career entrants in merchandising are recruited from other academic disciplines as well, the findings cannot necessarily be generalized across other disciplines. The extent to which the results would generalize to other populations is unknown, as data were collected from students who were new labor-market entrants. College recruitment is a major source of hiring for new labor-market entrants, and firms devote considerable resources to improving their reputation on college campuses. Steps were taken to maximize the realism and generalizability of the study while retaining the clear advantages of an experimental design. Relevant job attributes were taken directly from grain merchandisers from different-sized firms to improve the realism and generalizability of social, professional, and behavioral career aspects. Another strength of this study was the integration of discrete choices through involving job scenarios and using a multivariate technique that was useful to examine trade-offs made by individual respondents who were facing a range of options.

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Teaching and Educational Methods

Assessing Student Learning Using a Digital Grading Platform

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Abstract
Effective assessment of student learning is challenging for several reasons. Not only do learning assessments usually crowd out instructional time, but it can be difficult to assess higher-order cognitive aspects of student learning. In this commentary, I present a method for assessing student learning through the use of a digital grading platform that addresses both of these issues. I discuss a case study where this method was implemented and utilized to inform course design, and I argue that digital grading platforms expand instructors' options for student learning assessments.

1 Introduction

As instructors, we pursue parallel goals: on the one hand, we want our students to learn specific course content; on the other hand, we want our students to think about the world in fundamentally new ways. In a microeconomics course, for example, we want our students to learn how to use demand and supply curves to determine a market-equilibrium quantity and price. But more broadly, we want our students to understand more deeply the human behavior underpinning market outcomes: that incentives matter, that decisions are made on the margin, that opportunity costs are more relevant than accounting costs, and so on. Through assignments and exams, it is comparatively easy to assess whether our students have mastered course content. It is more difficult to assess whether students have mastered higher-order aspects of cognitive processing. In this commentary, I outline a method for assessing a wide variety of student learning outcomes through the use of a digital grading platform. Specifically, I present a case study in which this method was used to inform course design. The assessment method requires no additional effort by students, and minimal additional effort by instructors, making it a high-value approach to assessing student learning.

1.1 Standards of Learning

Today, it is fairly standard pedagogical practice for instructors to identify several student learning objectives (SLOs) in their courses. Ideally, instructors share these objectives with their students and use the SLOs to inform learning assessments like assignments and exams (Wiggins and McTighe 2005; Banta et al. 2009). An effective set of SLOs will incorporate a variety of learning functions. To borrow from Bloom's classic taxonomy of educational objectives, these could include knowledge, comprehension, application, analysis, synthesis, and evaluation (Bloom et al. 1956).[1] In short, SLOs outline an instructor's goals for a course, and effective assessment will refer back to these goals.

Beyond individual courses, SLOs can also exist for academic programs or entire institutions. For example, a program of study may specify a set of learning objectives for its students to achieve before graduation. When properly designed, course-level SLOs support and contribute to program- or institution-

[1] Bloom's original taxonomy has shortcomings, and subsequent scholarship has proposed an update that includes "creation" as the highest form of cognition (Anderson and Krathwohl 2001). There are also other approaches to categorizing learning. See, for example: Marzano (2001), Erickson et al. (2006), Fry et al. (2009), Biggs and Tang (2011), and Fink (2013).

level SLOs and vice versa (Suskie 2018, pp. 63–84). Consequently, methods that support course-level learning assessment can make it easier to assess higher-level SLOs as well. This in turn can help administrators satisfy institutional reporting requirements around student learning.

In practice, it can be challenging to assess SLOs—especially those objectives that pertain to higher-order aspects of cognition. One issue is that traditional learning assessments (assignments, tests, student surveys, etc.) require time and effort that can detract from instruction activities. Another issue is that traditional quantitative assessments can be poorly suited to measure students' ability to analyze, synthesize, and evaluate information beyond a particular application. In order to overcome these issues, one approach is to integrate the assessment of student learning into existing course activities in order to make efficient use of students' and instructors' time and effort. For example, an instructor can write exam questions that specifically link particular aspects of course content with particular SLOs. This allows the instructor to grade the exams both for mastery of content and achievement of learning objectives.

Indeed, so-called integrated assessment systems can improve teaching pedagogy (Atwood and Singh 2018) and are increasingly becoming a best practice for the assessment of student learning. Such systems are integrated into a course curriculum, embedded in course content, and economical to implement (Birenbaum et al. 2006). Increasingly, technology is making integrated assessment possible through computer-assisted assessment and similar methods (Brown et al. 1999). Such approaches fit naturally in courses where students or instructors are already making heavy use of technology for instruction, coursework, assignments, or exams (Seden 1999). Nonetheless, there remains a need for new methodologies to integrate computer-assisted assessment with other traditional and technology-based teaching and learning methods (Bull 1999), and to assess the full range of student learning and cognitive development. In this commentary, I address this need by presenting a method of assessing SLOs through the use of a digital grading platform. Tech-savvy instructors who teach large courses can easily implement my proposed method and improve the effectiveness of their existing assessment activities while simultaneously supporting institutional reporting of program-level SLOs. The remainder of this article is dedicated to a case study in which I discuss the implementation and evaluation of this method. I conclude by offering some thoughts about when and how the method can be most successfully applied in other settings.

2 Case Study: Background

Several years ago, I was involved in the assessment of a new introductory course in data science at a large public university. The course was conceived as a more holistic approach to data science education on campus than previous course offerings and was initially cross-listed between the computer science and statistics departments. A team of administrators, course instructors, and other campus stakeholders was convened to assess the new course and offer suggestions for future improvement. This team initially developed several high-level questions to guide its work: (1) what did we *want* students to learn in this introductory data science course; (2) what were students *actually* learning in the course; (3) how did the course and its content relate to other curricula on campus; and (4) what role(s) did it play?

To address these questions, I designed and implemented an integrated method to assess student learning in the course. As an initial step, I collaborated with one of the primary instructors to identify a list of SLOs. We settled on twelve distinct objectives, listed in figure 1. The objectives spanned several levels of cognitive thinking from application ("Calculate specified statistics of a given data set") to evaluation ("Given the result of a statistical analysis from the course, form correct conclusions about a question based on its meaning"). The SLOs also addressed dispositional learning objectives, such as "Articulate the benefits and limits of computing technology for analyzing data and answering questions." Once we had finalized the list of SLOs, the next step was to figure out how to assess whether students were achieving them.

The course was large, with roughly four hundred students enrolled in the spring semester's single section. Each week, students attended three lectures and a lab that could be completed in person or remotely. Thematically, the course was organized into several units: (1) data science—an overview of data

Upon completion of this course, students should be able to:

1. Write correct small programs that manipulate and combine data sets and carry out iterative procedures.
2. Extend a program with multiple functions so that it runs correctly with additional functionality.
3. Calculate specified statistics of a given data set.
4. Identify the sources of randomness in an experiment.
5. Formulate a null hypothesis that relates to a given question, which can be assessed using a statistical test.
6. Carry out statistical analyses including computing confidence intervals and performing hypothesis tests in a variety of data settings.
7. Given the result of a statistical analysis from the course, form correct conclusions about a question based on its meaning.
8. Given a question and an analysis, explain whether the analysis addresses the question and how the analysis could change and still address the question.
9. Articulate the benefits and limits of computing technology for analyzing data and answering questions.
10. Correctly generate and interpret histograms, bar charts, and box plots.
11. Correctly make predictions using regression and classification techniques.
12. Assess the accuracy and variability of a prediction.

Figure 1: List of student learning objectives

science; (2) tables—using Python to manipulate information; (3) visualization—interpreting and exploring data through visualizations; (4) sampling—understanding the behavior of random selection; (5) prediction—making predictions from data; (6) inference—reasoning about populations by computing over samples; and (7) probability—making assumptions and exploring their consequences.

In order to accommodate the course's large size, the instructor utilized Gradescope: a digital grading platform developed by several of the instructor's former students.[2] Students enrolled in the course completed their work electronically or by hand on a standardized template, and uploaded a PDF of their completed assignment into Gradescope. At that point, instructors or teaching assistants graded each assignment using a common grading rubric. The rubric was precise, breaking down individual problems into multiple predetermined components, each with their own point values. The course instructor adopted Gradescope primarily to increase grading efficiency among the course's teaching assistants, and to simplify the calculation and management of students' grades.[3]

In order to assess SLOs, I utilized the "assignment statistics" tool in Gradescope. For each distinct question or subquestion that could be graded, I determined whether the question addressed any of the twelve SLOs. I then tagged each question with one or more keywords associated with the SLOs. For example, a question that required students to adapt a piece of python code they had already written in order to add a new column to a data set would be tagged with SLOs 1 and 2: "write correct small programs that manipulate and combine data sets and carry out iterative procedures," and "extend a program with

[2] https://gradescope.com/

[3] For a detailed summary of Gradescope's capabilities, see Singh et al. (2017). At the time, the university's course management system (CMS) did not offer the same digital grading capabilities as Gradescope. Today, CMS products like Canvas and others provide similar options for digital grading in a large course.

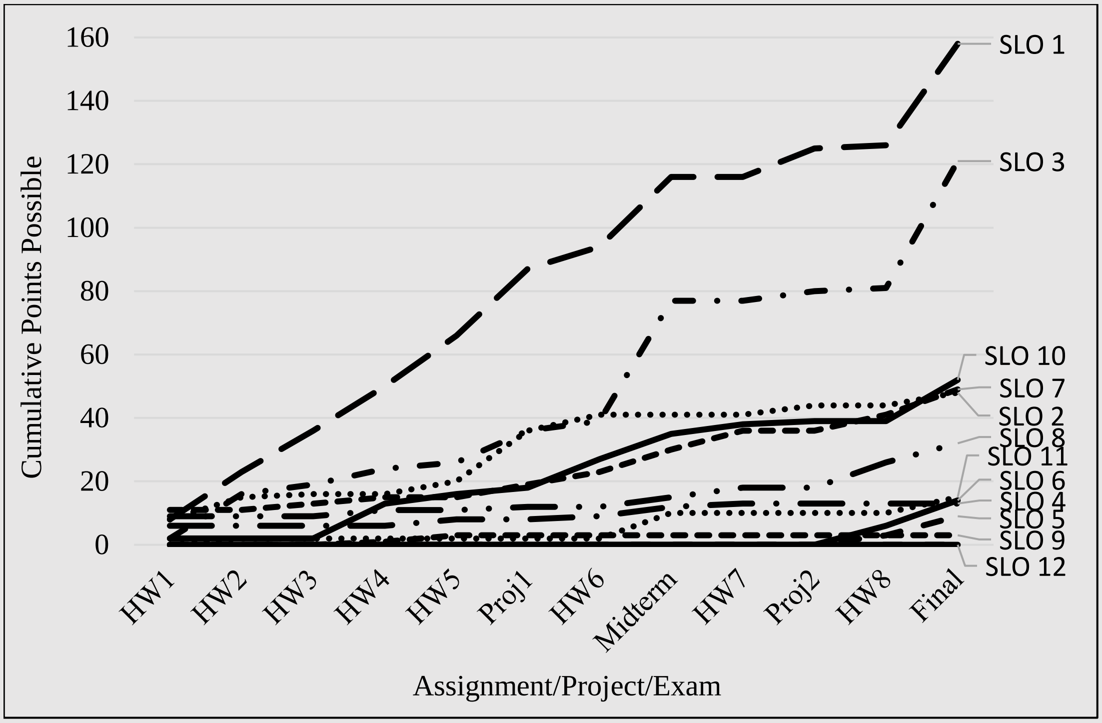

Figure 2: Cumulative points possible by student learning objective (SLO)

multiple functions so that it runs correctly with additional functionality." Once all students' assignments had been graded, Gradescope allowed me to view summary statistics about how students had performed on the questions tagged with each individual SLO. Specifically, I could easily determine how many possible points had been associated with each SLO in the assignment, and how students had performed overall on the questions associated with each SLO.[4]

3 Case Study: Results and Discussion

Over the course of the semester studied, there were a total of 337 possible points students could earn. Overall, students earned on average 82 percent of the points possible in the course. Keep in mind while interpreting the results below that each question in each assignment, project, or exam could have addressed zero, one, or multiple different SLOs.

Table 1 reports assessment results organized both by individual assignment and for the course overall. Several patterns quickly emerge. First, it is clear that most assignments addressed only a handful of the twelve SLOs. The final exam was an exception, in that it addressed nine of the twelve SLOs. Second, several SLOs were much more heavily stressed throughout the course than others, as evidenced by the number of points assigned to each SLO in the "Total" column. This is also visually apparent in figure 2, which shows the cumulative points possible by SLO across different assignments, projects, and exams. SLOs 1 and 3—those focused on writing programs and calculating statistics—were reflected in 158 and 121 points, respectively, throughout the semester. Next, SLOs 2, 7, and 10 were each reflected in roughly 50 points each. And SLO 12, which focused on assessing prediction accuracy, was not captured by any course question. Third, when a particular SLO was included in several sequential assignments, students tended to perform better on the objective over time. Consider, for example, SLO 1 over the first five assignments. As students gained more practice writing programs in python code, they got better at it.

[4] At the time of this case study, Gradescope's tagging capability was not widely available in other CMSs. Now, an increasing number of products are offering similar functionality. For example, instructors using Canvas can achieve similar ends using Gauge, an optional assessment management system (https://www.canvaslms.com/gauge/).

Table 1: Quantitative assessment of student learning objectives (SLOs)

SLO	Assignment 1 Points[a]	Assignment 1 % Correct[b]	Assignment 2 Points	Assignment 2 % Correct	Assignment 3 Points	Assignment 3 % Correct	Assignment 4 Points	Assignment 4 % Correct	Assignment 5 Points	Assignment 5 % Correct	Project 1 Points	Project 1 % Correct	Assignment 6 Points	Assignment 6 % Correct
1. Write programs	8	87	15	89	13	94	14	91	16	95	21	81	7	86
2. Extend a program	8	87	7	92	1	95	-	-	4	89	16	78	5	83
3. Calculate statistics	2	96	14	89	3	91	5	79	2	95	10	66	3	91
4. Identify sources of randomness	6	87	-	-	-	-	-	-	2	90	-	-	1	98
5. Form a null hypothesis	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6. Statistically test a hypothesis	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7. Form correct conclusions	11	84	-	-	2	84	2	88	-	-	4	68	4	92
8. Identify appropriate analyses	9	84	-	-	-	-	2	88	-	-	1	93	-	-
9. Articulate benefits and limits of computing	-	-	-	-	-	-	1	80	2	97	-	-	-	-
10. Generate graphs	2	83	-	-	-	-	11	82	3	84	2	74	9	91
11. Make predictions	-	-	2	78	-	-	-	-	-	-	-	-	-	-
12. Assess prediction accuracy	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Total[c,d]	27	89	25	91	13	100	21	89	22	97	23	85	17	92

SLO	Midterm Points	Midterm % Correct	Assignment 7 Points	Assignment 7 % Correct	Project 2 Points	Project 2 % Correct	Assignment 8 Points	Assignment 8 % Correct	Final Exam Points	Final Exam % Correct	TOTAL Points	TOTAL % Correct
1. Write programs	22	67	-	-	9	96	1	73	32	68	158	82
2. Extend a program	-	-	-	-	3	99	-	-	4	70	48	84
3. Calculate statistics	38	60	-	-	3	92	1	73	40	70	121	72
4. Identify sources of randomness	3	87	1	87	-	-	-	-	-	-	13	88
5. Form a null hypothesis	-	-	-	-	-	-	3	83	6	60	9	68
6. Statistically test a hypothesis	-	-	-	-	-	-	6	89	8	63	14	74
7. Form correct conclusions	7	70	6	86	-	-	5	93	8	60	49	79
8. Identify appropriate analyses	3	87	3	93	-	-	8	82	6	67	32	82
9. Articulate benefits and limits of computing	-	-	-	-	-	-	-	-	-	-	3	91
10. Generate graphs	8	43	3	84	1	95	-	-	13	71	52	75
11. Make predictions	8	67	-	-	-	-	-	-	5	71	15	70
12. Assess prediction accuracy	-	-	-	-	-	-	-	-	-	-	0	-
Total	45	64	11	94	26	97	17	88	90	68	337	82

[a] "Points" signifies "points possible" for each SLO (rows 1–12) or in total for an assignment/project/exam (Total row).
[b] "% Correct" signifies the average proportion of possible points earned across all students for each SLO or in total for an assignment/project/exam (**Total** row).
[c] Any question can address zero, one, or multiple SLOs. Therefore, the numbers in the **Total** row need not match the data in rows 1–12.
[d] Extra credit points are available, but do not contribute to any SLO. This is why the "% Correct" value in the Total row may appear unduly large.

The results in table 1 provided the information necessary for course instructors to adjust their curriculum in future semesters. For example, it became clear that instructors would either need to remove assessing prediction accuracy as a SLO, or better integrate it into the coursework. The same conclusion was drawn for SLO 9: articulating the benefits and limits of computing technology. Alternatively, it became clear that hypothesis testing—a core topic for the course—was only being introduced at the very end of the semester. Instructors decided to cover that material sooner in subsequent offerings of the course.

The fundamental value of the results in table 1 is that they reflect course content and student performance in terms of SLOs, rather than in terms of specific exercises or assignments. While the course instructor likely had a good sense of whether students had mastered various aspects of the python coding language, my analysis provided insight into whether students were achieving higher-order objectives, such as their ability to draw appropriate conclusions from data in a general sense. This information was a powerful tool for directing future course offerings, and my method could even be applied throughout a single semester to provide an instructor with real-time feedback about students' learning.

A digital grading platform with tagging functionality such as Gradescope or Gauge is key for this approach to be feasible. Indeed, once such a platform is adopted to support the grading process, little additional effort is required to tag individual questions and analyze those tags' resulting statistics. In the future, digital grading platforms could offer yet more powerful analytic tools, potentially even tracking student-level performance on SLOs over various assignments. In the era of big data, course instructors will be able to take advantage of easily accessible analytics.

4 Conclusion

Once a course instructor decides to adopt a digital grading platform with the ability to tag specific questions, it can be straightforward to effectively assess student learning by linking individual questions to predetermined SLOs. Such an approach addresses two long-standing barriers to effective learning assessment: (1) the extra work usually needed to assess students' learning, and (2) the complex nature of some higher-order learning objectives. While the case study presented in this commentary is specific to data science, the underlying method can be easily applied to almost any field of study. Economics is particularly well-suited to such an approach since it combines tangible skills (mathematics, graphing, calculation, etc.) with higher-order cognitive concepts (utility maximization, budget constraints, weighing marginal trade-offs, etc.).

More broadly, there are many benefits from adopting digital grading—especially in large classes. There are returns to scale both in the efficiency of grading each student's work (Anglin et al. 2008) as well as in the ability to analyze the resulting data. For these reasons, I predict that applied economics instructors will increase their adoption of digital grading platforms in the coming years. As I have demonstrated in this commentary, doing so will open doors to new and powerful methods for assessing student learning outcomes.

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Teaching and Educational Methods

Calculating and Interpreting Percentage Changes for Economic Analysis

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Abstract
A strong understanding of calculating and interpreting percentage changes and growth rates is critically important for economists. This is because many fundamental concepts such as the time value of money, and many commonly reported economic measures, such as the rate of return on assets, price inflation, and measures of economic growth, require a firm understanding of percentage changes. This paper presents a brief primer on calculating and interpreting percentage changes and growth rates. The purpose is to illuminate these measures, facilitate their interpretation, and clarify their usage for economic analysis.

1 Introduction

A strong understanding of calculating and interpreting percentage changes and growth rates is critically important for economists. This is because many fundamental concepts such as the time value of money, and many commonly reported economic measures, such as the rate of return on assets, price inflation, and measures of economic growth, require a firm understanding of percentage changes. Furthermore, economists tend to focus their economic analysis on relative changes of variables of interest rather than absolute changes. Arguably the most important measures in economics are elasticities, which come in many different varieties and represent the percentage change in one economic variable given a one-percent change in another.

This paper presents a brief primer on calculating and interpreting percentage changes and growth rates. The purpose is to illuminate these measures, facilitate their interpretation, and clarify their usage for economic analysis. Four alternative metrics of percentage change are discussed and compared using a simple numerical example. Some parsimonious suggestions are provided for preferring certain measures over others given the nature of the data series under investigation and the purpose of the analysis.

2 Measures of Percentage Change

The analysis of economic data often involves the need to calculate and interpret percentage changes. Some economic data are volatile with large fluctuations between data points, others are more smooth-trending with less variation. The alternative measures of percentage change discussed in this paper can differ substantially depending on the type of economic data series under investigation.

2.1 Fundamental Formulas for Calculating a Percentage Change

As a starting point consider three alternative methods of calculating a total percentage change in a data series, $x_0, x_1, \dots, x_T$. The total percentage change from x_0 to x_T can be calculated on different bases as follows:

Beginning Base: $$\%\Delta x_B = \frac{(x_T - x_0)}{x_0} \tag{1}$$

$$\textit{Average Base:} \qquad \%\Delta x_A = \frac{(x_T - x_0)}{0.5 \times (x_0 + x_T)} \tag{2}$$

$$\textit{Natural Log Base:} \qquad \%\Delta x_L = \ln\left(\frac{x_T}{x_0}\right). \tag{3}$$

Equation (1) uses the beginning period as the base, Equation (2) uses the average base of the beginning and ending periods, and Equation (3) uses the natural logarithm formula. Note that the average base of the beginning and ending periods is a discrete approximation to the continuous analog using natural logarithms, $\%\Delta x_A \cong \%\Delta x_L$. The approximation is good for small changes, but the metrics can be different for large percentage increases as shown in the numerical example that follows.

2.2 Growth Rates

Now consider the discrete compound interest formula that is familiar to economists, relating the present value to the future value of an asset, x. Let i denote the discount rate obtained using discrete compounding.[1]

$$x_T = x_0(1+i)^T \tag{4}$$

Solving for i gives:

$$i = \left[\frac{x_T}{x_0}\right]^{\frac{1}{T}} - 1. \tag{5}$$

We can use Equation (5) to calculate the annual average percentage change (growth rate) in the value of some asset over time. We can also use Equation (5) to calculate the rate of return to some investment opportunity, where x_0 is the present value of the cash outflows, and x_T is the future value of cash inflows. In this case, Equation (5) is called the modified internal rate of return (MIRR) of the investment, which was first introduced in the academic literature in the eighteenth century (Duvillard 1781; Biondi 2006). The more commonly reported measure of the rate of return in the economics literature is the internal rate of return (IRR). Typically, a closed analytical solution does not exist for calculating a conventional IRR (when cash inflows and outflows occur over numerous periods), and numerical methods like interpolation must be used to derive a solution.

The preference of reporting an IRR or a MIRR depends on the application. With an IRR, all of the cash inflows generated over the lifetime of a project are assumed to be reinvested in the project under analysis, which is probably a reasonable assumption when evaluating a targeted investment for a private company. By contrast, the MIRR allows for the incorporation of both an assumed cost-of-debt capital to calculate the present value of cash outflows (x_0 in Equation 5), as well as a potentially alternative reinvestment rate to calculate the future value of cash inflows (x_T in Equation 5). The MIRR is probably more appropriate for evaluating things like public investments in research and development (R&D), which have a cost-of-debt capital that can be pegged to the return on government bonds, and a reinvestment rate that represents a market rate of return.[2]

[1] Denote the value of an asset at time zero x_0. At discount rate, i, the value of the asset at the end of the first period is, $x_0 + x_0 i = x_0(1+i)$. The value at the end of the second period is, $x_0(1+i) + x_0(1+i)i = x_0(1+i)^2$. The value at the end of period T is, $x_0(1+i)^T$.

[2] There was a recent debate in the agricultural economics literature about the best method to evaluate the economic rate of return to public investments in agricultural R&D. Traditionally, most studies reported an IRR (Alston et al. 2000); however, Alston et al. (2011) and Hurley et al. (2014) argued that the MIRR is a superior measure for evaluating public investments in agricultural R&D. In a comment

Next consider the continuously compounded interest formula using the discount rate, r, and the base of the natural logarithms the mathematical constant, e,

$$x_T = x_0 e^{rT} \tag{6}$$

Solving for r gives:

$$r = \frac{\ln\left[\frac{x_T}{x_0}\right]}{T}. \tag{7}$$

The continuously compounded discount rate is $\%\Delta x_L$ divided by the total number of periods minus one (or data points minus one). We can use Equation (7) to calculate the annual average percentage change in x_t. We can also set the discrete compound interest formula equal to the continuously compounded interest formula to solve for the relationship between the discount rates,

$$(1+i)^T = e^{rT} \tag{8}$$

$$i = e^r - 1. \tag{9}$$

Equation (9) is the commonly used formula for calculating the discrete equivalent to a continuously compounded discount rate. Equations (5) and (7) show that the annual average percentage change in a data series is totally dependent on the choice of endpoints. We denote these the *endpoint* metrics of percentage change. This is not the case in the calculation of growth rates using regression analysis as in the next section, where all of the data points affect the estimated growth rate.

2.3 Trend Analysis

Consider the following specification of the population regression line, where the natural log of the dependent variable x_t is a linear function of a trend variable, t, and a random error term, u_t,

$$\ln x_t = \alpha + \beta t + u_t. \tag{10}$$

The random error terms are independent and identically distributed random variables that follow the normal distribution with conditional expectation equal to zero and constant variance, $u_t \sim N[0, \sigma^2]$. The first-order partial derivative of $\ln x_t$ with respect to the time variable represents the growth rate of x_t,

$$\frac{\partial \ln x}{\partial t} = \beta. \tag{11}$$

The ordinary least squares (OLS) point estimator of the population parameter β is an estimate of the growth rate of x_t and can be compared with an annual average percentage change as described in the previous section. The regression estimate uses all the data points in contrast to the *endpoint* metrics of percentage change. Any large outliers in the data or substantial volatility in the underlying data series can cause large differences in these measures.[3]

3 Numerical Example

to the Hurley et al. (2014) paper, Oehmke (2017) made the case that the IRR is still the preferred measure. Hurley et al. (2017) responded that the MIRR is the superior measure for evaluating public expenditures on R&D.

[3] In the case of the trend regression, additional estimation problems such as autocorrelation may be present that can bias the estimated growth rate.

A simple numerical example is presented to illustrate the concepts covered in the previous section. Table 1 shows two hypothetical data series used in the analysis that follows and the natural logarithms of each series. The endpoints for Data Series (1) and Data Series (2) are the same: $x = 10$ at $t = 1$, and $x = 16$ at $t = 10$. Data Series (1) is a relatively volatile series with large annual fluctuations, and Data Series (2) is a relatively smooth-trending series except for a single large outlier (large decrease in year 8).

Table 1. Two Hypothetical Data Series and Natural Logs

Data series (1)			Data series (2)		
t	x	$\ln x$	t	x	$\ln x$
1	10	2.30	1	10	2.30
2	13	2.56	2	11	2.40
3	9	2.20	3	11	2.40
4	15	2.71	4	12	2.48
5	12	2.48	5	11	2.40
6	16	2.77	6	13	2.56
7	15	2.71	7	14	2.64
8	17	2.83	8	10	2.30
9	22	3.09	9	15	2.71
10	16	2.77	10	16	2.77

Figure 1 shows each of the hypothetical data series, the natural log of each series, and a linear trend added to the natural log series. The figure also includes the estimated linear trend equation and the corresponding R^2 for each data series.

The results from an OLS regression of $\ln x_t$ on a time trend using Data Series (1) are presented below in Equation (12),

$$\ln x_t = \underset{(0.1164)}{2.2642} + \underset{(0.0188)}{0.0690t} \qquad \underset{(s.e.)}{T = 10} \tag{12}$$

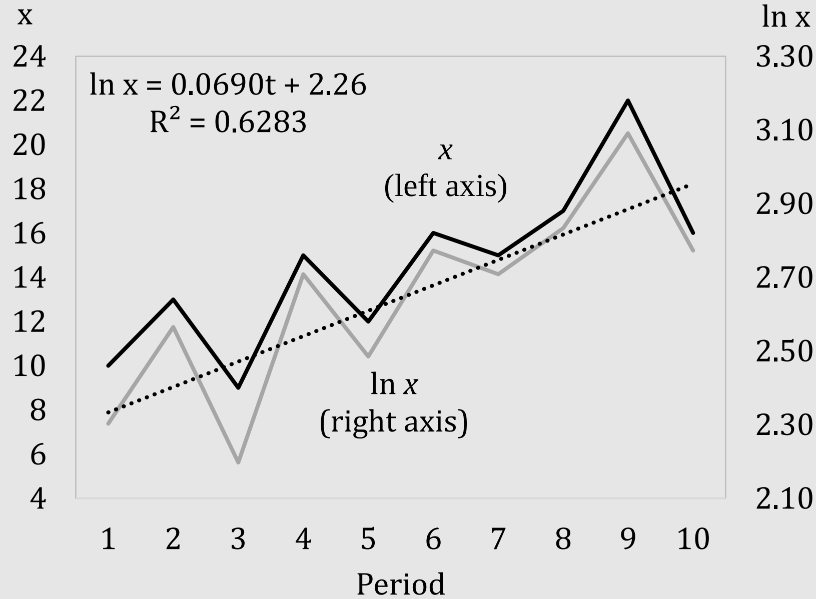
The standard errors are in parentheses. The $R^2 = 0.6283$, and the estimated growth rate $\hat{\beta} = 0.0690$ is statistically significantly different from zero at the 1-percent level of significance. Note that $\hat{\beta}$ represents a continuously compounded discount rate analogous to the previously defined, r, and Equation (9) can be used to convert to a discrete discount rate, i, if this is preferred. In the current application, the equivalent rate under discrete compounding is $i = 0.0714$ or 7.14 percent per period.

Table 2 shows the total percentage change and the growth rate for each metric using Data Series

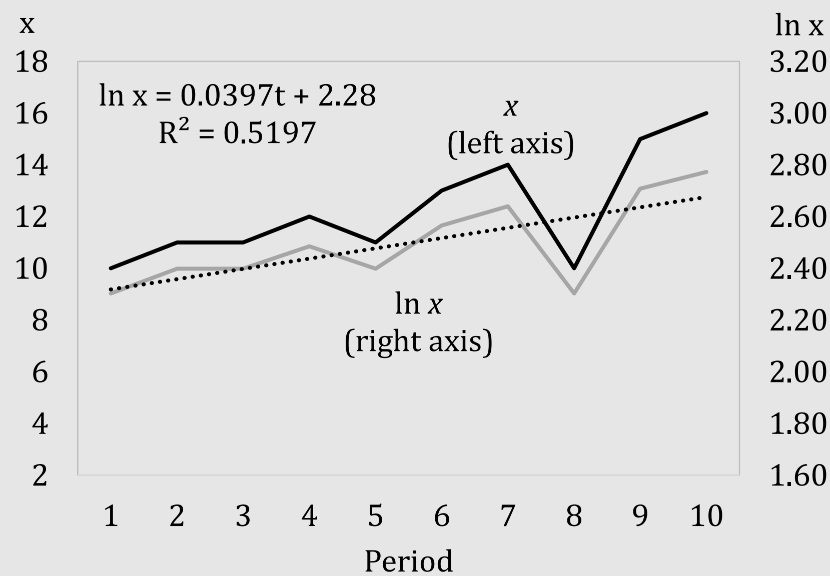
Table 2: Percentage Changes and Growth Rates for Alternative Metrics for Data Series (1)

Panel (a): Endpoint $t = 10$			Panel (b): Endpoint $t = 9$		
Metric	Total	Annual-average	Metric	Total	Annual-average
Beginning base	60.00	6.67	Beginning base	120.00	15.00
Average base	46.15	5.13	Average base	75.00	9.38
Natural log	47.00	5.22	Natural log	78.85	9.86
Regression	62.10	6.90	Regression	67.28	8.41

Note: The beginning, average, and natural log estimates are from Equations (1), (2), and (3). The regression estimates are from Equation (10). The point estimates of total percent change = $\hat{\beta} \times (t-1)$.



(a) Data Series 1 and Linear Trend



(b) Data Series 2 and Linear Trend

Figure 1. Hypothetical Data with Linear Trend for Natural Log Series

Note: The figures include the linear trend equation and the R^2. The estimated growth rate from the linear trend regression in Data Series (1) is 6.90 percent, which is statistically significantly different from zero at the 1-percent level of significance. In Data Series (2), the estimated growth rate is 3.97 percent, which is statistically significantly different from zero at the 5-percent level of significance.

(1) and two different endpoints for the analysis, $t = 9$ and $t = 10$. The first three rows of each panel in Table 2 show the calculated percentage changes using Equations (1), (2), and (3), and their corresponding growth rates.

The final row of each panel is the point estimator of the growth rate from Equation (10). In Table 2 Panel (a), when t = 10, the three *endpoint* metrics of the growth rate range from 5.13 to 6.67 percent. In Panel (b), when t = 9, the *endpoint* metrics range from 9.38 to 15.00 percent. This is an example of the sensitivity of standard measures of percentage change to the choice of endpoint, and the potential for "cherry-picking" a desired result. Also note that the discrete approximation to the natural log formula is accurate for modest increases in the data series x_t as in Panel (a), but the two measures diverge for large increases as in Panel (b). If we report the regression estimates of the growth rate for both endpoints (t = 9 and t =10), which use all of the data, the estimate does not change as drastically falling from 8.41 to 6.90 percent. This is a case where the regression estimate of the growth rate has a clear advantage over the alternatives. When working with volatile data series, the choice of the range of data under analysis is critically important, especially when using metrics that depend solely on the endpoints to calculate the growth rate.

Next, we turn to hypothetical Data Series (2) in Table 1 and Figure 1, to illustrate the effects of a substantial outlier in the data series. Recall the endpoints of each of the Data Series (1) and (2) are the same, x = 10 at t = 0 and x = 16 at t = 10; therefore, the first three metrics of the percentage change and the growth rate (the beginning period base, average base, and natural log) are the same as in Table 2 Panel (a). Only the regression estimate of the growth rate differs between the two data series. In Data Series (1), the point estimate of the growth rate is 6.90 percent, and in Data Series (2) the estimate falls to 3.97 percent. The large single outlier in Data Series (2) caused a dramatic reduction in the point estimate of the growth rate. The regression estimate of the growth rate is sensitive to large outliers in the data, and this is an important cautionary note when using and interpreting these measures.

To summarize, be cautious when reporting standard measures of percentage change such as those calculated using the beginning period base or the natural logarithm formula when the choice of endpoints is important. This is especially true when analyzing data series that vary significantly from year to year as in hypothetical Data Series (1). In this case, a regression estimate is likely the optimal option. Conversely, if the data series is mostly smooth-trending, but has a significant outlier like in Data Series (2), a regression estimate of the growth rate will be substantially impacted.[4] In this case the standard measures are superior. These results should serve as a cautionary tale about the importance of understanding measures of percentage change, and in particular which method was used to construct the measures.

4 Conclusion

Important economic measures such as inflation rates, elasticities, the rate of return on assets, and interest rates, represent the percentage change of some underlying economic data series. Are the measures total percentage changes, annual averages, or regression estimates, and which method was used to calculate them? Do the metrics represent continuous compounding or discrete compounding? As an economic practitioner, the author suggests the natural log formula (Equation 3) to calculate a total percentage change, as well as an estimate of the annual average after dividing by the number of periods minus one; however, in addition, a regression estimate of the growth rate is sometimes obtained. The difference between the annual average and the regression estimate of the growth rate will be large when the data are volatile or there are significant outliers in the data. A good rule of thumb is to use a standard measure of percentage change like a natural log formula when the data series under analysis is relatively smooth-trending, the data series has a large outlier, or the choice of endpoints is not of particular importance. The regression estimate of the growth rate is superior when the data are volatile and the choice of endpoints is important to the analysis.

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[4] It is also possible to use a dummy variable for a large outlier year if there is a justification.

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Teaching and Educational Methods

Enhancing the Teaching of Product Substitutes/Complements: A Pedagogical Note on Diversion Ratios

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Keywords: Diversion ratios, demand systems, cross-price elasticities, identification of next-best substitutes

Abstract
Application of diversion ratios in demand analysis has received little attention. Even microeconomic textbooks typically do not address this topic. The literature review presented here shows use of diversion ratios, along with cross-price elasticities, to study the price effects associated with mergers and acquisitions, a practice recommended to measure product substitutability/complementarity. With the aim of expanding experiential learning in the fields of applied economics, agricultural economics, and agribusiness, this article demonstrates how diversion ratios can be calculated from any uncompensated own-price and cross-price elasticity matrix derived from the analysis of demand systems, and it discusses the teaching of this concept in the classroom.

1 Introduction

In analyzing the impact of a tax on consumption or a merger on competition, it is useful to assess the degree of substitution between one good and a number of other goods. Typically, cross-price elasticities of demand are used to identify the degree of substitutability or complementarity among goods. These elasticities often relate to the closeness of substitutes. Consider a per-unit cigarette tax designed to reduce tobacco consumption. Suppose that the cross-price elasticity between cigarettes and cigars is 0.5, whereas the cross-price elasticity between cigarettes and chewing tobacco is 5.0. On the basis of the values of the aforementioned cross-price elasticities, we would conclude that chewing tobacco and cigarettes are more closely related than cigarettes and cigars. The elasticities allow us to compare percentages, but the relative magnitudes of the changes in terms of percentages can be misleading when translated to quantities as the following example suggests.

Suppose that the quantity demanded of cigars is the equivalent of 1,000 pounds of tobacco, whereas the quantity demanded of chewing tobacco is the equivalent of 10 pounds of tobacco. Given the respective cross-price elasticities, if the price of cigarettes were to increase 10 percent, the quantity demanded of cigars would increase 50 pounds, whereas the quantity demanded of chewing tobacco would increase by only 5 pounds. When actual quantities are taken into account, the better substitute for cigarettes in terms of the equivalent quantity of tobacco is cigars rather than chewing tobacco.[1] The alternative measure introduced here, the diversion ratio, allows us to make this comparison.

Alternative measures for identifying substitutes (or complements) on the basis of actual quantities, emerged from the industrial organization literature, specifically the literature on the competitive effects of mergers (a focus of antitrust enforcement) (Shapiro 1996; Werden 1998). Werden (1998, 405) provides five measures for ranking substitutes on the basis of unit diversion or dollar diversion. The unit diversion

[1] A similar argument was articulated by Ault et al. (2005) in considering the use of cross-price effects to study the effectiveness of smokeless tobacco in smoking cessation.

ratio relates the increase in unit sales of substitute product *j* relative to the decrease in unit sales of product *i*. Alternatively, the dollar diversion ratio represents the increase in dollar sales of substitute *j* relative to the decrease in dollar sales of product *i*. Relatively little is known about diversion ratios outside of the fields of antitrust economics or industrial organization. In fact, diversion ratios typically are not even addressed in microeconomic textbooks.

Given the proliferation of product differentiation strategies in agricultural and food markets, stakeholders are keen to understand which products are substitutes for each other. To help stakeholders better coordinate their production and marketing decisions, analysts would need to know whether or not two or more substitutes are "equally close" to a given product, that is, whether the substitutes would experience the same change in quantity or dollar sales in response to a change in the price of the base product.

If impacts of quantity-wise movement among products are of interest, we suggest the use of diversion ratios. But if impacts of percentage changes in prices of various products are of interest, the concept of cross-price elasticities would be of greater utility. Together, diversion ratios and cross-price elasticities can be used to measure product substitutability/complementarity in demand analysis.

This articles presents the concept of diversion ratios and reviews the literature on applications of the ratios in applied economic analyses. It demonstrates that diversion ratios are a natural byproduct of the estimation of demand systems, describes certain characteristics of the ratios, and shows how, using an empirical example, the concept of the ratios can be taught in the classroom.

2 The Concept of Diversion Ratio

According to Werden (1998), the term *diversion ratio* appears to have been introduced by Shapiro (1996). But the idea and its relevance were discussed five years earlier by Willig (1991). Shapiro (1996) reported that the diversion ratio was used by antitrust enforcement agencies to analyze "unilateral effects" in mergers involving differentiated products, that is, the tendency of a horizontal merger to lead to higher prices simply by virtue of the fact the merger will eliminate the direct competition between the merging firms (even if all other firms in the market continue to compete independently). The diversion ratio concept currently is considered by the Department of Justice and the Federal Trade Commission in the United States, the European Commission, and the Competition Bureau in Canada.

Diversion ratios provide a perspective different from that of conventional cross-price elasticities on identifying substitutes or complements. The *unit diversion ratio* is the change in the quantity of one good attributed to a change in the quantity of another good. If a consumer buys one less unit of a good as a result of, say, an increase in the price of that good, *ceteris paribus*, to where would that consumption be diverted? Alternatively, what happens to the consumption of other goods as a result of this increase in price? It may be of strategic value to know the quantity-wise response of one good to a change in the quantity of another good.

Consider two goods, i and j. We want to determine the change of quantity of good j attributed to the change of quantity of good i, both measured in the same units (say, gallons or ounces). Mathematically, we can describe this relationship as follows:

$$DR_{ji} = \frac{\partial q_j}{\partial q_i} \tag{1}$$

where DR_{ji} refers to the diversion ratio of good j with respect to good i, and ∂q_j is the change in the quantity of good j and ∂q_i is the change in the quantity of good i.

Let us assume that the price of the ith good changes (i.e., ∂p_i). It is likely to affect both good i and good j. This relationship can be captured in equation (1) by rewriting it as follows:

$$DR_{ji} = \frac{\frac{\partial q_j}{\partial p_i}}{\frac{\partial q_i}{\partial p_i}}. \tag{2}$$

Multiplying both the numerator and denominator by p_i / q_j and upon further simplification, we obtain the following:

$$DR_{ji} = \frac{\frac{\partial q_j}{\partial p_i}\frac{p_i}{q_j}}{\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_j}} = \frac{e_{ji}}{\frac{\partial q_i}{\partial p_i}\frac{p_i}{q_j}\frac{q_i}{q_i}} = \frac{e_{ji}}{e_{ii}}\frac{q_j}{q_i}. \tag{3}$$

On the basis of equation (3), the diversion ratio is a function of e_{ji}, which represents the uncompensated cross-price elasticity of demand for good *j* with respect to a change in the price of good *i*, e_{ii}, which represents the own-price elasticity of demand for good *i* and the ratio of the quantity of good *j* to the quantity of good *i*. Like own-price and cross-price elasticities, diversion ratios vary, empirically, from observation to observation.

Likewise, the *dollar diversion ratio*, defined as the change in the dollar sales of product *j* relative to a change in the dollar sales of product *i*, can be expressed mathematically as follows; $e_{ji}p_jq_j/e_{ii}p_iq_i$, where p_i is the price of product *i* and p_j is the price of product *j*. This metric can be expressed as $DR_{ji} * \frac{p_j}{p_i}$. In other words, the dollar diversion ratio describes where the dollar sales are diverted, as a result of a decrease in sales of one good due to, say, a public policy measure like taxes on sugar-sweetened beverages, for example.

Finally, the relative unit (or relative dollar) diversion ratio relates the increase in unit (or dollar) sales of substitute product *j* relative to the decrease in unit sales of base product *i* proportionate to their relative quantity or dollar-sales shares, as a result of a change in the price of the base product. To arrive at this measure, the unit diversion ratio (or the dollar diversion ratio) simply is multiplied by the share of product *i* relative to the share of product *j*.

3 Applications of Diversion Ratios from the Extant Literature

To illustrate the specific use of diversion ratios, we draw examples from the economic literature with respect to industrial organization (applications to antitrust issues), new product introductions, and taxation of sugar-sweetened beverages. According to Shapiro (1996), the diversion ratio between Brand A and Brand B is a key variable in determining post-merger market competitiveness, because this metric relates the change in the consumption of Brand B attributed to a change in consumption of Brand A.

To support this contention, consider a situation in which Brands A and B each have pre-merger prices of $100 and pre-merger sales of 1,000. Suppose that a 10 percent price increase by Brand A leads to a 25 percent reduction in units sold. As the price of Brand A rises, some customers will shift from Brand A to Brand B. Prior to the merger, these customers would be lost to the firm owning Brand A. Therefore, the number of sold Brand A units is now 750. Hence, the revenue pre-merger accruing to Brand A is now $82,500, down from $100,000, as a result of the 10 percent price increase.

Now consider a merger between brands A and B. After the merger, the firm owning Brand A now also owns Brand B and thus does not lose customers for Brand B. Suppose that the diversion ratio from Brand A to Brand B is 70 percent. Consequently, of the 250 units lost by Brand A due to the price increase, 70 percent, or 175 units, are diverted to Brand B. The merged entity would take into account the additional revenue earned by Brand B when considering the price increase from $100 to $110. Assuming that the price of Brand B also rises to $110, the diverted sales of 175 units generate a revenue stream of $19,250. Adding this amount to the pre-merger revenue of $82,500 yields the post-merger revenue of $101,750. Bottom line: the merger yields additional revenue of $1,750 above the pre-merger level as a consequence of the 10 percent price increase. In this example, a 10 percent price hike will generate more revenue after the merger only if the diversion ratio is at least 63.64 percent.

Werden (1998) described the use of own-price and cross-price demand elasticities and diversion ratios in the analysis of mergers and acquisitions (antitrust analysis), although he did not provide empirical examples. In 2010, the horizontal merger guidelines issued jointly by the U.S. Department of Justice and the U.S. Federal Trade Commission were the first to explicitly incorporate the concept of diversion ratios (U.S. Department of Justice 2010).

Abere et al. (2002) used the concept of diversion ratio (unit as well as dollar diversion ratio) to investigate ex-ante market competition analysis of the acquisition of Cadbury Schweppes' carbonated soft drinks by the Coca-Cola company in Canada. In that analysis, diversion ratios were used to identify the next-best substitute products, defined as the products that would account for the largest-volume loss as a result of a reduction in price competitiveness due to the proposed acquisition. Abere et al. (2002) generated diversion ratios using own-price and cross-price elasticities obtained from the Rotterdam and linear approximated almost ideal demand system (LA/AIDS) models, hence two diversion ratios for each beverage were considered. According to the calculated diversion ratios, the next-best substitute products for Cadbury Schweppes' carbonated soft drinks were fruit juices and fruit drinks (those with the largest diversion ratios).

Yuan et al. (2009) estimated cross-price elasticities as well as unit and dollar diversion ratios in assessing the demand for functional food products. They investigated potential cannibalization in the orange juice category resulting from introduction of a new functional orange juice product, Minute Maid Heart Wise. Would sales of conventional Minute Maid products be diminished as a result of the launch of the Minute Maid Heart Wise product? The analysis using unit and dollar diversion ratios revealed that introduction of Minute Maid Heart Wise would not cannibalize sales or volumes of existing Minute Maid orange juice products. However, sales and volumes of competing brands of Minute Maid products, namely Florida's Natural and Tropicana, would be diminished. This result is indicative of decreasing quantities of Florida's Natural and Tropicana brands as a result of the introduction of Minute Maid Heart Wise. In other words, according to the calculated diversion ratios, the next-best substitute products for Minute Maid Heart Wise were, in order, Tropicana and Florida's Natural. Additionally, the sum of all diversion ratios indicated that introduction of the phytosterol-enriched Minute Maid Heart Wise product increased volumes of all orange juice category products by 0.46 units. In other words, consumers now purchase more orange juice than they did before the introduction of Minute Maid Heart Wise.

Dharmasena and Capps (2012) used the concept of unit diversion ratios and dollar diversion ratios to shed light on where the consumer is diverted when a gallon of sugar-sweetened beverages (carbonated soft drinks, sports drinks, and fruit drinks) is removed from the consumption bundle as a result of a beverage tax.[2] Details of this study are presented in the "An Applied Example" below.

4 Diversion Ratios as a Natural Byproduct of the Estimation of Demand Systems

The use of demand systems applications is widespread in the economics literature. A survey of these systems was provided by Barnett and Serletis (2008). Popular demand systems include the almost ideal demand system (AIDS) (Deaton and Muellbauer 1980), direct or indirect translog models (Christensen and Lau 1975), the Rotterdam model (Barten 1964; Theil 1965), the Barten synthetic model (Barten 1993), the quadratic almost ideal demand system (QUAIDS) (Banks, Blundell, and Lewbel 1997), and the exact affine

[2] Taxes may not necessarily remove just one unit of sugar-sweetened beverages. One unit is a representative measure used for simplicity of explanation.

stone index (EASI) inverse Marshallian demand system (Lewbel and Pendakur 2009). The calculation of unit diversion ratios or dollar diversion ratios is a natural byproduct of the estimation of any demand system.[3] From equation (3), the unit diversion ratio is related to the ratio of the cross-price elasticity of good *j* with respect to the price of good *i* relative to the own-price elasticity of good *i*.

The principal product of demand systems is the estimation of the matrix of own-price and cross-price elasticities. If attention is centered on any column of the uncompensated own-price and cross-price elasticity matrix, the calculation of diversion ratios for that column is initiated by dividing any cross-price elasticity in that column by the corresponding own-price elasticity of that column. Subsequent multiplication of the ratio of the respective quantities yields the unit diversion ratio. Consequently, given the matrix of own-price and cross-price elasticities derived through the estimation of any demand system, the calculation of diversion ratios is a straightforward exercise. Once matrices of elasticities have been produced through the estimation of demand systems, diversion ratios can be calculated with simple arithmetic.

5 Characteristics of Diversion Ratios

We draw attention to several characteristics of diversion ratios. First, the diversion ratio for any good with respect to itself is 1. Second, for substitute products, the diversion ratio is *negative*, and for complementary goods, the diversion ratio is *positive*. Third, the sum of the diversion ratios in any given column may be zero, positive, or negative. In general, the sum of diversion ratios is not equal to zero. Finally, tests of significance of any diversion ratio may be based on the use of the Delta method, a method for approximating the variance/standard error of the diversion ratio. Bootstrapping methods also may be applicable in this capacity. Any diversion ratio corresponds to a nonlinear combination of estimated coefficients of the demand system, associated prices, and associated quantities. Consequently, the statistical distribution to be used in testing the significance of any diversion ratio rests on the use of a chi-squared distribution with one degree of freedom.

6 An Applied Example

We illustrate the identification of next-best substitutes using unit diversion ratios and dollar diversion ratios for 10 non-alcoholic beverages featured in the work by Dharmasena and Capps (2012). Specific categories of non-alcoholic beverages considered were isotonics (sports drinks), regular soft drinks (non-diet soft drinks), diet soft drinks, high-fat milk (whole and 2 percent milk), low-fat milk (1 percent and skim milk), fruit drinks, fruit juices, bottled water, coffee, and tea. Policymakers' interest is in knowing where the consumer would be diverted if a gallon of regular soft drinks were removed from the consumption bundle as a result of a tax on those drinks. The set of uncompensated elasticities gleaned from the use of the linear approximated quadratic almost ideal demand system model (LA/QUAIDS) is exhibited in Table 1.

Interest is centered on sugar-sweetened beverages, namely isotonics, regular soft drinks, and fruit drinks. To calculate the unit diversion ratios with respect to regular soft drinks, for example, we initially divide all elasticities in the regular soft drinks column in Table 1 by the own-price elasticity of regular soft drinks. Second, we multiply these ratios by the respective quantity ratios to obtain diversion ratios of all beverages with respect to regular soft drinks. Negative signs associated with the unit diversion ratios delineate the decrease (increase) in the quantity of one good due to a unit increase (decrease) in the quantity of another good, hence substitutability between goods. On the other hand, a positive sign associated with the unit diversion ratios describes the decrease (increase) in the quantity of one good due

[3] The Allen elasticity of substitution is also a natural byproduct of demand systems. This notion is given by e_{ij}^*/w_j, where e_{ij}^* is the compensated cross-price elasticity of demand and w_j is the budget share of the j^{th} good. This measure provides a symmetric substitution matrix.

Table 1. Estimated uncompensated own- and cross-price elasticities generated from the linear approximated quadratic almost ideal demand system model (LA/QUAIDS) estimated by Dharmasena and Capps (2012)[a]

	Isotonics	Regular soft drinks	Diet soft drinks	High-fat milk	Low-fat milk	Fruit drinks	Fruit juices	Bottled water	Coffee	Tea
Isotonics	**-3.8650**	-0.1216	2.2073	-0.8598	0.5235	**-2.4720**	**1.9803**	0.3722	1.0631	-0.0021
	(0.8227)	(1.3177)	(1.3857)	(0.8888)	(0.7879)	(0.7470)	(1.0876)	(0.7639)	(0.7736)	(0.4210)
	[0.0000]	[0.9268]	[0.1168]	[0.3375]	[0.5092]	**[0.0016]**	**[0.0740]**	[0.6279]	[0.1749]	[0.9960]
Regular soft drinks	-0.0088	**-2.2552**	**-0.6208**	0.0424	**0.2373**	**-0.1663**	**1.0338**	-0.0543	**0.2181**	0.0555
	(0.0609)	(0.2679)	(0.1916)	(0.1153)	(0.1005)	(0.0948)	(0.1683)	(0.1071)	(0.1151)	(0.0666)
	[0.8852]	**[0.0000]**	**[0.0020]**	[0.7146]	**[0.0218]**	**[0.0847]**	**[0.0000]**	[0.6143]	**[0.0632]**	[0.4083]
Diet soft drinks	0.1509	**-0.8550**	**-1.2721**	**0.3856**	-0.1722	**0.3726**	-0.0963	**0.2475**	-0.0051	-0.0121
	(0.0957)	(0.2821)	(0.3167)	(0.1569)	(0.1363)	(0.1312)	(0.1878)	(0.1321)	(0.1371)	(0.0752)
	[0.1205]	**[0.0037]**	**[0.0002]**	**[0.0171]**	[0.2117]	**[0.0063]**	[0.6101]	**[0.0661]**	[0.9707]	[0.8727]
High-fat milk	-0.0544	0.1964	**0.4359**	**-0.7591**	0.2989	**-0.2219**	**-0.5556**	0.0173	-0.0185	**-0.1452**
	(0.0595)	(0.1708)	(0.1542)	(0.2170)	(0.1971)	(0.0803)	(0.1253)	(0.0846)	(0.0902)	(0.0504)
	[0.3641]	[0.2549]	**[0.0065]**	**[0.0009]**	[0.1350]	**[0.0077]**	**[0.0000]**	[0.8388]	[0.8378]	**[0.0056]**
Low-fat milk	0.0558	**0.6358**	-0.2009	0.4435	**-0.9237**	-0.1448	**-0.4669**	-0.1537	-0.0209	-0.0793
	(0.0806)	(0.2263)	(0.2036)	(0.2996)	(0.2942)	(0.1004)	(0.1552)	(0.1038)	(0.1101)	(0.0597)
	[0.4916]	**[0.0068]**	[0.3279]	[0.1444]	**[0.0027]**	[0.1549]	**[0.0039]**	[0.1441]	[0.8501]	[0.1894]
Fruit drinks	**-0.2934**	-0.3659	**0.6436**	**-0.4501**	**-0.2044**	**-0.6892**	0.0786	**-0.3446**	**0.4709**	-0.0912
	(0.0888)	(0.2424)	(0.2269)	(0.1406)	(0.1154)	(0.1860)	(0.1977)	(0.1602)	(0.1812)	(0.0922)
	[0.0017]	[0.1368]	**[0.0063]**	**[0.0023]**	**[0.0821]**	**[0.0005]**	[0.6925]	**[0.0358]**	**[0.0119]**	[0.3270]
Fruit juices	**0.1069**	**1.2844**	-0.0141	**-0.4326**	**-0.2370**	0.0683	**-1.1731**	-0.0769	**-0.2526**	-0.0775
	(0.0585)	(0.2006)	(0.1494)	(0.0996)	(0.0808)	(0.0910)	(0.1889)	(0.1052)	(0.1103)	(0.0658)
	[0.0730]	**[0.0000]**	[0.9250]	**[0.0000]**	**[0.0049]**	[0.4559]	**[0.0000]**	[0.4681]	**[0.0258]**	[0.2437]
Bottled water	0.0566	0.0318	**0.5864**	0.0721	-0.1784	**-0.3424**	-0.1532	**-0.7540**	-0.0455	0.1965
	(0.1027)	(0.3143)	(0.2603)	(0.1677)	(0.1337)	(0.1840)	(0.2606)	(0.2899)	(0.2144)	(0.1282)
	[0.5842]	[0.9199]	**[0.0282]**	[0.6687]	[0.1876]	**[0.0680]**	[0.5589]	**[0.0119]**	[0.8329]	[0.1310]
Coffee	0.1203	**0.6977**	0.0962	0.0166	0.0128	**0.4856**	**-0.4584**	-0.0312	**-1.6459**	**0.2442**
	(0.0839)	(0.2743)	(0.2188)	(0.1444)	(0.1157)	(0.1683)	(0.2214)	(0.1737)	(0.2456)	(0.1079)
	[0.1571]	**[0.0138]**	[0.6620]	[0.9091]	[0.9120]	**[0.0055]**	**[0.0431]**	[0.8580]	**[0.0000]**	**[0.0274]**
Tea	0.0019	0.3359	0.0117	**-0.4200**	-0.1524	-0.1192	-0.2967	0.2448	**0.3893**	**-0.9104**
	(0.0784)	(0.2713)	(0.2067)	(0.1385)	(0.1072)	(0.1462)	(0.2244)	(0.1771)	(0.1847)	(0.1540)
	[0.9804]	[0.2207]	[0.9552]	**[0.0037]**	[0.1607]	[0.4184]	[0.1915]	[0.1724]	**[0.0395]**	**[0.0000]**

Source: Dharmasena and Capps (2012).

[a] Estimated elasticities in bold font indicate statistical significance at the 0.10 level. Standard errors are shown in parentheses, and p-values are shown in square brackets.

to a unit decrease (increase) in the quantity of another good, hence complementarity between goods. Table 2 exhibits the calculated unit diversion ratios associated with the respective non-alcoholic beverage categories, and it includes calculated standard errors and *p*-values.

Let us assume the consumer is responding to the proposed tax on sugar-sweetened beverages by consuming fewer regular soft drinks. For every gallon of regular soft drinks taken away from the consumer, consumption of low-fat milk would increase by 0.11 gallons; fruit juices, by 0.29 gallons; and coffee, by 0.32 gallons. Consumption of diet soft drinks would decrease by 0.26 gallons. If, as a result of the tax, the consumption of isotonics were reduced by a gallon, the consumption of fruit drinks would decrease by 0.81 gallons. However, the consumption of fruit juices would increase by 0.50 gallons. A tax-induced decrease in the consumption of a gallon of fruit drinks would reduce the consumption of isotonics by 0.34 gallons; high-fat milk, by 0.66 gallons; and bottled water, by 0.94 gallons. On the other hand, a decrease in the consumption of fruit drinks would increase consumption of diet soft drinks and coffee by 1.26 gallons and 2.52 gallons, respectively.

The tax policy on non-alcoholic beverages is not a zero-sum game, because the calculated diversion ratios within any column do not sum to zero (see the column sum estimate reported in Table 2). The tax on regular soft drinks decreases the consumption of non-alcoholic beverages by 0.47 gallons in total, all other factors invariant. The tax on isotonics increases the consumption of non-alcoholic beverages by 0.97 gallons in total, whereas the tax on fruit drinks decreases the consumption of non-alcoholic beverages by 0.34 gallons in total, *ceteris paribus*.

Table 3 presents the calculated dollar diversion ratios for the respective non-alcoholic beverage categories. As a result of a tax on sugar-sweetened beverages, every dollar decrease in sales of regular soft drinks would increase sales of high-fat milk by 6 cents; low-fat milk, by 13 cents; fruit juices, by 51 cents; coffee, by 14 cents; and tea, by 3 cents. Consumers would spend 91 cents more on diet soft drinks, 22 cents more on fruit juices, and 80 cents more on coffee for every dollar of spending diverted from fruit drinks. Further, for every dollar diverted from isotonics as a result of tax on sugar-sweetened beverages, consumers would spend 52 cents more on diet soft drinks, 13 cents more on low-fat milk, 48 cents more on fruit juices, 28 cents more on coffee, and 9 cents more on bottled water.

To clarify further, for every dollar diverted from isotonics, consumers would spend a total of $1.51 more on diet soft drinks ($0.52), low-fat milk ($0.13), fruit juices ($0.48), bottled water ($0.09), and coffee ($0.28), see Table 3). However, consumers would spend a total of $1.83 less on isotonics ($1.00), regular soft drinks ($0.04), high-fat milk ($0.19), and fruit drinks ($0.60). Consequently, consumers would spend 32 cents less on all non-alcoholic beverages as a result of a tax on isotonics (see the column total for isotonics in Table 3). Similarly, for every dollar diverted from regular soft drinks as a result of a tax, consumers would spend 45 cents less on all beverages (see the column total for regular soft drinks in Table 3). Similarly, for every dollar diverted from fruit drinks as a result of a tax, consumers would spend $1.38 less on all beverages (see the column total for fruit drinks in Table 3).

Table 5 exhibits the next-best substitutes for the 10 respective beverage products based on compensated cross-price elasticities and unit diversion ratios. For five of these products, the next-best substitutes identified by compensated cross-price elasticities (shown in Table 4) differ from those identified by unit diversion ratios. For diet soft drinks, the next-best substitute is high-fat milk according to compensated cross-price elasticities but bottled water according to unit diversion ratios. For isotonics and fruit drinks, the next-best substitute is diet soft drinks according to cross-price elasticities but coffee according to unit diversion ratios. For regular soft drinks, the next-best substitute is fruit juices according to compensated cross-price elasticities but coffee according to unit diversion ratios. Finally, the next-best substitute for tea is regular soft drinks according to cross-price elasticities but coffee according to unit diversion ratios.

Interestingly, compensated cross-price elasticities and unit diversion ratios identify the same next-best substitutes for high-fat milk, low-fat milk, fruit juices, bottled water, and coffee. For high-fat.

Table 2. Unit diversion ratios calculated from the LA/QUAIDS model estimated by Dharmasena and Capps (2012)[a]

	Isotonics	Regular soft drinks	Diet soft drinks	High-fat milk	Low-fat milk	Fruit drinks	Fruit juices	Bottled water	Coffee	Tea
Isotonics	1	0.0015	-0.0699	0.0522	-0.0390	**0.3379**	**-0.0926**	-0.0246	-0.0170	0.0002
		(0.0161)	(0.0423)	(0.0545)	(0.0575)	(0.1466)	(0.0469)	(0.0544)	(0.0120)	(0.0316)
		[0.9267]	[0.1040]	[0.3419]	[0.5004]	**[0.0249]**	**[0.0534]**	[0.6526]	[0.1626]	[0.9960]
Regular soft drinks	0.0829	1	**0.7136**	-0.0935	**-0.6417**	0.8252	**-1.7537**	0.1302	**-0.1269**	-0.1509
	(0.5697)		(0.3330)	(0.2531)	(0.3128)	(0.5469)	(0.2669)	(0.2744)	(0.0667)	(0.1760)
	[0.8848]		**[0.0365]**	[0.7133]	**[0.0449]**	[0.1370]	**[0.0000]**	[0.6369]	**[0.0622]**	[0.3949]
Diet soft drinks	-0.9691	**0.2593**	1	**-0.5816**	0.3185	**-1.2641**	0.1117	**-0.4062**	0.0020	0.0225
	(0.5833)	(0.0911)		(0.2615)	(0.2702)	(0.4503)	(0.2227)	(0.2112)	(0.0546)	(0.1399)
	[0.1022]	**[0.0062]**		**[0.0302]**	[0.2434]	**[0.0069]**	[0.6178]	**[0.0595]**	[0.9707]	[0.8727]
High-fat milk	0.3053	-0.0520	**-0.2993**	1	**-0.4829**	**0.6576**	**0.5630**	-0.0248	0.0064	**0.2361**
	(0.3338)	(0.0432)	(0.1120)		(0.1955)	(0.3154)	(0.1561)	(0.1202)	(0.0313)	(0.0904)
	[0.3643]	[0.2341]	**[0.0098]**		**[0.0166]**	**[0.0416]**	**[0.0007]**	[0.8373]	[0.8377]	**[0.0116]**
Low-fat milk	-0.2098	**-0.1129**	0.0924	**-0.3915**	1	0.2876	**0.3170**	0.1477	0.0049	0.0864
	(0.2935)	(0.0356)	(0.0977)	(0.1832)		(0.2201)	(0.1000)	(0.1294)	(0.0256)	(0.0668)
	[0.4778]	**[0.0025]**	[0.3479]	**[0.0370]**		[0.1967]	**[0.0025]**	[0.2588]	[0.8496]	[0.2011]
Fruit drinks	**0.8058**	0.0475	**-0.2164**	**0.2904**	0.1617	1	-0.0390	**0.2419**	**-0.0801**	0.0726
	(0.3311)	(0.0325)	(0.0739)	(0.1310)	(0.0999)		(0.0979)	(0.1124)	(0.0254)	(0.0716)
	[0.0182]	[0.1494]	**[0.0049]**	[0.0308]	[0.1114]		[0.6919]	**[0.0357]**	**[0.0025]**	[0.3150]
Fruit juices	**-0.5047**	**-0.2862**	0.0082	**0.4794**	**0.3222**	-0.1703	1	0.0927	**0.0738**	0.1059
	(0.2529)	(0.0370)	(0.0865)	(0.1856)	(0.1398)	(0.2275)		(0.1423)	(0.0335)	(0.0977)
	[0.0508]	**[0.0000]**	[0.9252]	**[0.0124]**	**[0.0249]**	[0.4573]		[0.5173]	**[0.0315]**	[0.2829]
Bottled water	-0.2935	-0.0078	**-0.3725**	-0.0879	0.2666	**0.9387**	0.1437	1	0.0146	-0.2956
	(0.5608)	(0.0769)	(0.1613)	(0.2064)	(0.2281)	(0.4835)	(0.2525)		(0.0696)	(0.2037)
	[0.6028]	[0.9197]	**[0.0247]**	[0.6718]	[0.2474]	**[0.0572]**	[0.5716]		[0.8345]	[0.1524]
Coffee	-1.1799	**-0.3231**	-0.1154	-0.0382	-0.0363	**-2.5159**	**0.8120**	0.0782	1	**-0.6941**
	(0.8338)	(0.1234)	(0.2600)	(0.3332)	(0.3278)	(0.8262)	(0.4140)	(0.4456)		(0.2887)
	[0.1626]	**[0.0114]**	[0.6588]	[0.9092]	[0.9123]	**[0.0035]**	**[0.0548]**	[0.8613]		**[0.0195]**
Tea	-0.0073	-0.0601	-0.0054	**0.3739**	0.1664	0.2387	0.2031	-0.2372	**-0.0914**	1
	(0.2971)	(0.0471)	(0.0959)	(0.1516)	(0.1356)	(0.2852)	(0.1667)	(0.2016)	(0.0411)	
	[0.9804]	[0.2075]	[0.9552]	**[0.0167]**	[0.2251]	[0.4061]	[0.2280]	[0.2445]	**[0.0303]**	
Column Sum	-0.9699	**0.4663**	**0.7353**	**1.0033**	**1.0355**	0.3354	**1.2652**	**0.9980**	**0.7863**	**0.3831**
	(0.6066)	(0.1016)	(0.2632)	(0.3593)	(0.4110)	(0.5861)	(0.4361)	(0.4095)	(0.0571)	(0.2026)
	[0.1154]	**[0.0000]**	**[0.0071]**	**[0.0071]**	**[0.0146]**	[0.5693]	**[0.0053]**	**[0.0180]**	**[0.0001]**	**[0.0638]**

Source: Dharmasena and Capps (2012).

[a] Diversion ratios in bold font indicate statistical significance at the 0.10 level. Standard errors are shown in parentheses, and p-values are shown in brackets.

Table 3. Dollar diversion ratios calculated from the LA/QUAIDS model

	Isotonics	Regular soft drinks	Diet soft drinks	High-fat milk	Low-fat milk	Fruit drinks	Fruit juices	Bottled water	Coffee	Tea
Isotonics	1.0000	0.0027	-0.1292	0.0833	-0.0626	0.4512	-0.0963	-0.0805	-0.0712	0.0005
Regular soft drinks	0.0449	1.0000	0.7136	-0.0806	-0.5570	0.5962	-0.9878	0.2304	-0.2871	-0.2670
Diet soft drinks	-0.5244	0.2593	1.0000	-0.5016	0.2765	-0.9133	0.0629	-0.7187	0.0046	0.0398
High-fat milk	0.1915	-0.0603	-0.3470	1.0000	-0.4859	0.5509	0.3677	-0.0509	0.0169	0.4843
Low-fat milk	-0.1308	-0.1300	0.1065	-0.3890	1.0000	0.2394	0.2057	0.3010	0.0127	0.1761
Fruit drinks	0.6035	0.0657	-0.2995	0.3466	0.1942	1.0000	-0.0304	0.5923	-0.2509	0.1777
Fruit juices	-0.4848	-0.5081	0.0145	0.7342	0.4964	-0.2184	1.0000	0.2912	0.2966	0.3328
Bottled water	-0.0898	-0.0044	-0.2105	-0.0429	0.1308	0.3834	0.0457	1.0000	0.0187	-0.2956
Coffee	-0.2822	-0.1428	-0.0510	-0.0145	-0.0139	-0.8035	0.2022	0.0612	1.0000	-0.5428
Tea	-0.0022	-0.0340	-0.0031	0.1823	0.0816	0.0975	0.0647	-0.2371	-0.1169	1.0000
Net column sum	0.3257	0.4481				1.3834				

Source: Calculated by the authors on the basis of Dharmasena and Capps (2012).

Table 4. Estimated compensated own- and cross-price elasticities generated from the linear approximated quadratic almost ideal demand system model (LA/QUAIDS)[a]

	Isotonics	Regular soft drinks	Diet soft drinks	High-fat milk	Low-fat milk	Fruit drinks	Fruit juices	Bottled water	Coffee	Tea
Isotonics	**-3.8544**	0.1027	**2.3611**	-0.7024	0.6280	**-2.3827**	**2.1822**	0.4497	1.1617	0.0543
	(0.0000)	(0.9368)	(0.0950)	(0.4302)	(0.4331)	(0.0024)	(0.0553)	(0.5517)	(0.1421)	(0.8969)
Regular soft drinks	0.0048	**-1.9652**	**-0.4219**	**0.2459**	**0.3724**	-0.0509	**1.2950**	0.0460	**0.3457**	**0.1283**
	(0.9368)	(0.0000)	(0.0295)	(0.0388)	(0.0006)	(0.5887)	(0.0000)	(0.6645)	(0.0043)	(0.0568)
Diet soft drinks	**0.1622**	**-0.6151**	**-1.1075**	**0.5539**	-0.0604	**0.4681**	0.1198	**0.3304**	0.1005	0.0482
	(0.0950)	(0.0295)	(0.0009)	(0.0008)	(0.6625)	(0.0007)	(0.5361)	(0.0140)	(0.4699)	(0.5196)
High-fat milk	-0.0472	**0.3504**	**0.5415**	**-0.6510**	**0.3707**	**-0.1607**	**-0.4169**	0.0705	0.0492	**-0.1065**
	(0.4302)	(0.0388)	(0.0008)	(0.0039)	(0.0667)	(0.0489)	(0.0020)	(0.3996)	(0.5902)	(0.0369)
Low-fat milk	0.0635	**0.7992**	-0.0889	**0.5581**	**-0.8476**	-0.0798	**-0.3198**	-0.0973	0.0509	-0.0383
	(0.4331)	(0.0006)	(0.6625)	(0.0667)	(0.0059)	(0.4277)	(0.0497)	(0.3423)	(0.6486)	(0.5186)
Fruit drinks	**-0.2822**	-0.1280	**0.8068**	**-0.2833**	-0.0935	**-0.5945**	0.2928	-0.2624	**0.5755**	-0.0314
	(0.0024)	(0.5887)	(0.0007)	(0.0489)	(0.4277)	(0.0022)	(0.1553)	(0.1012)	(0.0027)	(0.7316)
Fruit juices	**0.1142**	**1.4380**	0.0912	**-0.3248**	**-0.1655**	0.1294	**-1.0348**	-0.0238	-0.1850	-0.0389
	(0.0553)	(0.0000)	(0.5361)	(0.0020)	(0.0497)	(0.1553)	(0.0000)	(0.8183)	(0.1015)	(0.5503)
Bottled water	0.0613	0.1330	**0.6558**	0.1432	-0.1312	-0.3021	-0.0621	**-0.7190**	-0.0009	**0.2220**
	(0.5517)	(0.6645)	(0.0140)	(0.3996)	(0.3423)	(0.1012)	(0.8183)	(0.0148)	(0.9966)	(0.0852)
Coffee	0.1245	**0.7860**	0.1567	0.0785	0.0540	**0.5207**	-0.3789	-0.0007	**-1.6071**	**0.2664**
	(0.1421)	(0.0043)	(0.4699)	(0.5902)	(0.6486)	(0.0027)	(0.1015)	(0.9966)	(0.0000)	(0.0153)
Tea	0.0102	**0.5107**	0.1315	**-0.2974**	-0.0710	-0.0497	-0.1393	**0.3052**	**0.4662**	**-0.8665**
	(0.8969)	(0.0568)	(0.5196)	(0.0369)	(0.5186)	(0.7316)	(0.5503)	(0.0852)	(0.0153)	(0.0000)

Source: Dharmasena and Capps (2012).

[a] Estimated elasticities in bold font indicate statistical significance at the 0.10 level. Standard errors are shown in parentheses.

Table 5. Identification of next-best substitutes calculated from compensated cross-price elasticities and quantity diversion ratios

Beverage category	Cross-price elasticity and diversion ratio	Isotonics	Regular soft drinks	Diet soft drinks	High-fat milk	Low-fat milk	Fruit drinks	Fruit juices	Bottled water	Coffee	Tea
Isotonics	Cross-price elasticities	-		x							
	Unit diversion ratios	-								x	
Regular soft drinks	Cross-price elasticities		-					x			
	Unit diversion ratios		-							x	
Diet soft drinks	Cross-price elasticities			-	x						
	Unit diversion ratios			-					x		
High-fat milk	Cross-price elasticities			x	-						
	Unit diversion ratios			x	-						
Low-fat milk	Cross-price elasticities		x			-					
	Unit diversion ratios		x			-					
Fruit drinks	Cross-price elasticities			x			-				
	Unit diversion ratios						-			x	
Fruit juices	Cross-price elasticities		x					-			
	Unit diversion ratios		x					-			
Bottled water	Cross-price elasticities			x					-		
	Unit diversion ratios			x					-		
Coffee	Cross-price elasticities		x							-	
	Unit diversion ratios		x							-	
Tea	Cross-price elasticities		x								-
	Unit diversion ratios									x	-

Source: Compiled by the authors on the basis of Dharmasena and Capps (2012). All the cross-price elasticities are compensated elasticities.

milk and for bottled water, the next-best substitute is diet soft drinks. For low-fat milk, fruit juices, and coffee, the next-best substitute is regular soft drinks.

7 Teaching Discussion

At what level of instruction and in what courses should the concept of diversion ratios be introduced? We advocate the teaching of diversion ratios in graduate-level microeconomics and industrial organization (IO) courses. The concept of cross-price elasticities in undergraduate classes typically poses problems for students. Consequently, introducing the concept of diversion ratios in undergraduate teaching programs is not recommended.

We have successfully taught the concept of diversion ratios in a graduate-level applied demand analysis class addressing estimation of demand systems and identification of product substitutes or complements. As noted above, calculation of unit diversion ratios or dollar diversion ratios is a natural byproduct of the estimation of any demand system, and use of diversion ratios adds measurably to discussion of unequivocal product substitutes or complements, an important topic given the proliferation of product differentiation strategies in agricultural and food markets. Given adoption of the diversion ratio concept by the Department of Justice and the Federal Trade Commission in the United States, the Competition Bureau in Canada, and the European Commission, teaching of the concept in any graduate-level IO course will enhance the marketability of graduate students, especially those seeking opportunities with these government agencies.

8 Conclusion

Diversion ratios are typically applied in industrial organization contexts and cross-price elasticities, in demand analyses. Use of diversion ratios in demand analysis has received little attention.

Unit diversion ratios and dollar diversion ratios can be calculated from the use of any uncompensated own-price and cross-price elasticity matrix derived from demand systems. Using ten beverage categories, we compared next-best substitutes identified on the basis of compensated cross-price elasticities and on the basis of unit diversion ratios. Our analysis shows that to understand the impacts of percentage changes in prices of various products, we ought to use conventional cross-price elasticities. However, to understand the impacts of quantity-wise movement among products, we ought to use diversion ratios.

We advocate increased use of the diversion ratio concept, along with Allen elasticities of substitution, to measure product substitutability/complementarity. Because calculation of diversion ratios is a natural byproduct of the application of demand systems, introduction of the diversion ratio concept in graduate-level microeconomics courses would enhance experiential learning. Given its adoption in the Horizontal Merger Guidelines in 2010, the concept should be taught in any IO graduate-level course.

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Teaching and Educational Methods

Teaching Undergraduate Economics: Emphasize Early the Meaning of Vertical Distances and of Their Summation Over Quantities

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Abstract
Many important economic concepts—for example, deadweight losses, market surplus measures, and concepts preceded by the word "total"—are graphically depicted as areas. Although many students can identify areas like total surplus appropriately in simple circumstances such as when a market is in equilibrium, many struggle to do so when the circumstances are even slightly more complex, such as when a market is not in equilibrium. The reason may be that many students do not understand how these areas are graphically derived. In this commentary, I discuss simple adjustments instructors can make to emphasize the economic meaning of vertical distances and of their summation over quantities so that students can better identify graphical representations of economic concepts even in more complex circumstances.

I teach an introductory environmental economics course for which a class in principles of microeconomics or its equivalent is a prerequisite. Many students in the course have already taken intermediate microeconomics as well. If students struggle in my course, certainly one of the leading reasons is because they are not accustomed to thinking about the economic meaning of vertical distances in graphs that measure dollars on the vertical axis and quantity of a good on the horizontal axis.

A common error is illustrated by Figure 1, which depicts a market in which there is a negative externality, as indicated by a marginal social cost (MSC) curve above the supply curve. When students are asked to depict the deadweight loss in surplus when the market is in equilibrium, many indicate the horizontally shaded triangle instead of the vertically shaded triangle. I suspect that many students make this mistake because they do not understand how deadweight losses in general are graphically derived (i.e., that they are a series of appropriate vertical distances added over quantities). Instead, they have learned in microeconomic principles class that a per-unit tax leads to a deadweight loss that looks like a triangle "pointing" to the right. In this commentary, I discuss these and other potential reasons that many undergraduate economics students likely struggle with the meaning of vertical distances. I also present ways that instructors can reinforce marginal analysis concepts.

One reason that students might struggle with the economic meaning of vertical distances is that some instructors introduce them to the "supply and demand" diagram before introducing them to the "marginal cost and marginal benefit" diagram, which of course is the same diagram. A demand curve (D) is an ordering of consumers from highest to lowest marginal benefit of consumption, and a supply curve (S) is an ordering of producers from lowest to highest marginal cost of production. Thinking about the curves in these two respective ways emphasizes different spatial relationships. Consider the "D" curve in demand terms: if you tell me a price, I can tell you the quantity demanded at that price, which is graphically a horizontal distance. Now consider the "D" curve in marginal benefit terms: if you tell me a quantity, I can

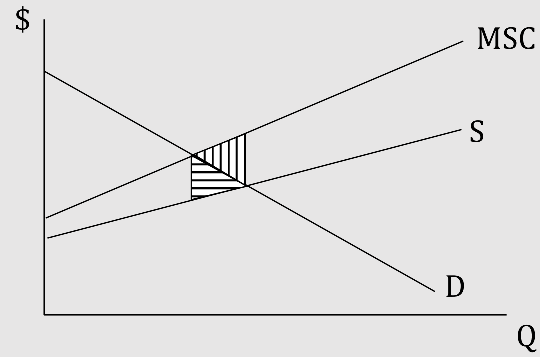


Figure 1. Which triangle is the deadweight loss when the market is at equilibrium?

tell you the marginal benefit of the last unit consumed, which is graphically a vertical distance.[1]

Perhaps some instructors explain supply and demand curves before marginal cost and marginal benefit curves because they want to quickly introduce students to the concept of market equilibrium. Equilibrium is much more straightforwardly explained by thinking of the diagram in supply and demand terms. When a good's price is too high, a quantity surplus results, so some bright seller gets the idea to reduce the price in order to sell the surplus and get it off the shelves. When a good's price is too low, another bright seller gets the idea to raise it because she can do so and still make a sale. This dynamic plays out until equilibrium is reached. Instructors frequently follow up this lesson by introducing elasticities.

However, in many cases, instructors could better serve student learning by using marginal cost and marginal benefit curves instead of supply and demand curves. These cases include those in which students are asked to consider whether a market makes people best off (as measured by total surplus), the conditions under which it fails to make them best off, and the policies that could improve or worsen market outcomes. In judging whether an action makes people better off—in this case, by deciding whether to produce and consume one more unit of a good—marginal benefits and costs are measured as vertical distances in the graph, not as horizontal distances. While experienced instructors naturally think this way, I believe there are three ways we can more effectively help our students to do the same.

First, we can ensure that definitions correspond with the vertical distances that are useful. For example, the microeconomics principles textbook by Mankiw (2015) defines *consumer surplus* as "the amount a buyer is willing to pay for a good minus the amount the buyer actually pays" (p. 137). Graphically this amount is the vertical distance between the marginal benefit curve and the price line at a particular unit. On the next page, consumer surplus is used to refer to an area in the graph: "The area below the demand curve and above the price measures the consumer surplus in a market" (p. 138). Mankiw explains that the area called consumer surplus is calculated by adding together the consumer surplus on each unit consumed, but he uses the same term to describe both the vertical distance relevant to a given single unit consumed and the area relevant to all units consumed. If, instead, we were to use a term such as *marginal consumer surplus* to describe the consumer surplus gained from consumption of a single unit (we use the word *marginal* to emphasize one unit in other economic situations, so why not here?), that surplus might be better established as an important unique concept. Indeed, marginal consumer surplus is arguably the more important concept because consumer surplus (the area) is just the summation of a bunch of marginal consumer surplus values. If a student forgets that relationship, he or she will have difficulty when the circumstances of the problem change.

[1] Relatedly, I find it easy to forget to remind students that it is assumed that each previous unit was allocated to the consumer who values it most. The parallel assumption applies to marginal cost.

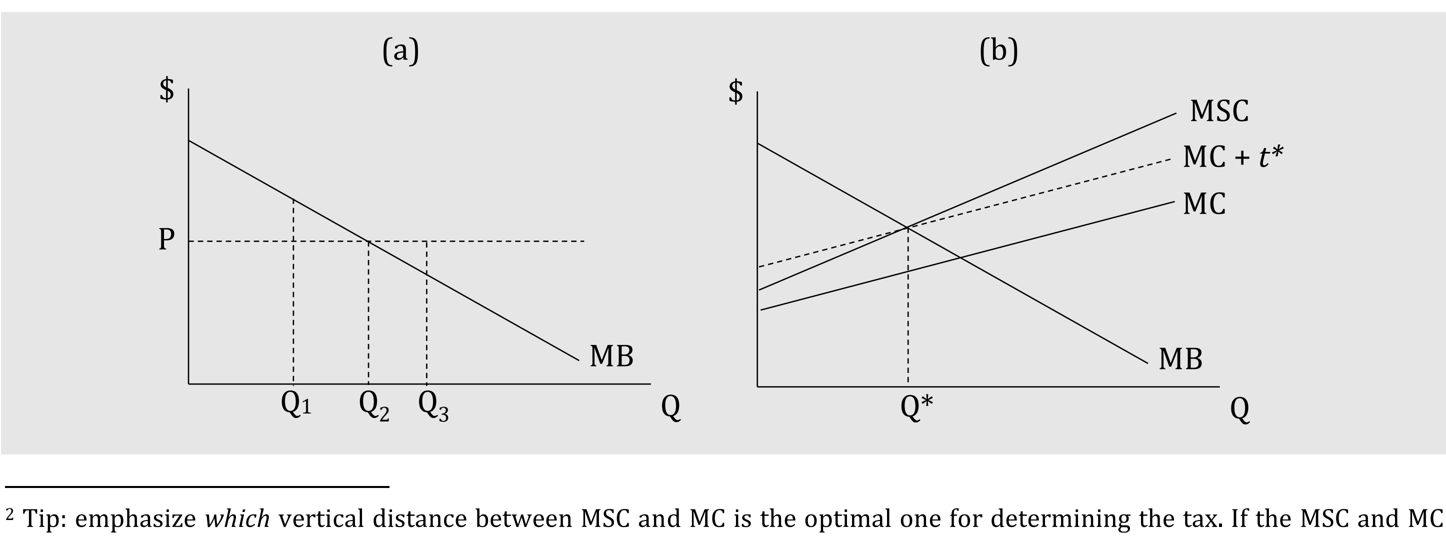
Second, as touched on above, we can consider the order in which we teach concepts. One possibility might be to first discuss market welfare impacts of different quantities of a good consumed and produced using a marginal cost and marginal benefit diagram and then to teach equilibrium using a supply and demand diagram. This order of presentation would seem to be preferable if there are more contexts in which it is natural to think of the curves as marginal cost and marginal benefit curves than contexts in which it is natural to think of them as supply and demand curves. The lesson of equilibrium might also then be more impactful because students should immediately recognize that the equilibrium maximizes total surplus (under the typical assumptions).

Third, we can label the curves to reflect how we would like students to think about them. In Figure 1 for instance, the supply and demand curves could instead be labeled MC and MB. Doing so may help reinforce for students that a curve with a label that starts with M likely signals that vertical distances will be important in the diagram.

Consider panel (a) of Figure 2, which depicts a marginal benefit (MB) curve, a given price, and three quantities of the good. Given the price, the area depicting consumer surplus is either a trapezoid (under Q_1), a triangle (Q_2), or a "bowtie" shape (Q_3), where the left side of the bowtie is positive consumer surplus and the right side is negative consumer surplus. Once the student has mastered the idea that consumer surplus is the sum of the marginal consumer surpluses for each unit—that is, a set of vertical distances—he or she will never get the area representing consumer surplus incorrect for a given Q. When the idea of adding vertical distances over quantities has not been mastered, students tend to rely on other means of determining the answer, like remembering that it was a triangle in the previous class example.

It is especially critical that students understand the economic meaning of vertical distances and of their summation over quantities in comparatively complex diagrams. One of the more complex graphs from an introductory course in environmental economics depicts an optimal Pigouvian tax in the presence of a negative externality, as in panel (b) of Figure 2. A vertical distance of central importance is the "marginal external cost," that is, the cost of the pollution from a given unit of the good, imposed on people external to the market transaction. The marginal social cost (MSC) curve simply sums, for each unit, the marginal cost of producing the unit (MC) and the marginal external cost of that unit. So, by algebra, the marginal external cost of a given unit is the vertical distance between the MSC and MC curves.

In a simple graph that depicts only a MB curve, a MC curve, and a MSC curve (i.e., panel (b) but without the dashed lines), students should be able to identify the economically efficient quantity of the good (the quantity at which the MB and the MSC are equal and therefore have the same vertical distance) and the optimal Pigouvian tax, t^* (equal to the vertical distance between the MSC and MC curves at the efficient quantity[2]), which maximizes total surplus. Table 1 lists several other important concepts relevant to this example, all of which are graphically derived by adding vertical distances over quantities.



[2] Tip: emphasize *which* vertical distance between MSC and MC is the optimal one for determining the tax. If the MSC and MC curves are drawn parallel, this point is lost.

Table 1. Concepts that are vertical distances added up over quantities

Concept	Relevant Vertical Distance	Geometric Shape[a]
consumer surplus	MB - P	triangle
producer surplus (under tax)	P - (MC + t)	triangle
total external cost	MSC - MC	trapezoid
total tax revenue	t	parallelogram (or rectangle)
deadweight loss if market *isn't* at Q*	MB - MSC (or MSC - MB)	N/A
total surplus	MB - MSC	triangle

Note: Each listed concept is an area that is found by adding up the relevant vertical distance over the appropriate number of units.
[a] The corresponding geometric shape in panel (b) assumes the market is at efficient quantity, Q*, but may be different under a different Q.

Figure 2. Consumer surplus at different quantities (a), taxing under a negative externality (b).

Students would have a much easier time graphically depicting these and other concepts in different economic contexts if they understood the economic meaning of vertical distances. In most introductory microeconomics textbooks, vertical distances on graphs (and their summation across units) are important in understanding numerous topics: market efficiency, the costs of taxation, international trade and tariffs, externalities, public goods and common resources, production and associated costs, profit maximization, deadweight losses from monopolies, and markets for factors of production, among others.

As a final argument for encouraging students to understand the economic meaning of vertical distances, consider the connection of those distances to integration, which students learn as they advance in the study of economics.[3] Adding up a bunch of vertical distances over a quantity is integration, so undergraduates who have learned integration and have been trained from the start to think of many economic concepts as summations of vertical distances over quantities can easily grasp the connection between economics and the mathematical tools we use to express it.

Table 2 lists an incomplete but reasonably representative assortment of introductory-level microeconomics textbooks, some more general and some with greater focus on agricultural contexts. The table is not intended to be a critique of the overall quality of these books, some of which are excellent; instead, it highlights each book's approach to the three ideas presented above to help students better relate marginal thinking to vertical distances. Clearly, the books in general do not adopt all the suggestions. However, a blanket recommendation to implement all the suggestions should not be inferred by the reader. For example, teaching students market welfare concepts graphically before teaching equilibrium may not suit many instructors, and even if it does, it might introduce other problems, for example, by not matching the order of presentation in the instructor's otherwise preferred textbook. On the other hand, using different terms to differentiate "marginal" consumer or producer surplus from "total" consumer or producer surplus would seem to be fairly innocuous. We generally will not accept students failing to distinguish between marginal cost and total cost just by using the word *cost*, so we should probably hold ourselves to the same standard when discussing surplus measures and other concepts when the distinction is useful.

My overall point is this: by thinking carefully about how our teaching—from what we say to what we write to what we draw—might affect students' thinking, we can adjust our teaching styles to best serve that thinking. For example, even when supply and demand curves are first introduced as such, instructors

[3] In my own department, undergraduate students are not required to learn integration as part of the major curriculum, but many do learn it if they take advanced calculus courses, and of course integration is necessary at the graduate level.

Table 2. What do microeconomic principles textbooks do?

Textbook authors	Does not use "consumer surplus" to refer to both a vertical distance and an area?	Market welfare covered graphically[a] before equilibrium?	Curves labeled "MC" and "MB" when discussing market-level welfare?
Acemoglu et al. (2015)	No	No	Yes and No[b]
Arnold (2019)	No	No[c]	No
Bade and Parkin (2015)	No[d]	No	Yes
Barkley and Barkley (2016)	No	No	No
Mankiw (2015)	No	No	No
Penson et al. (2015)	No	Yes	No

[a] Several books cover marginal thinking and analysis before equilibrium, just not graphically.
[b] Does so when covering producer surplus but not when covering consumer or total surplus.
[c] Does illustrate efficiency at the individual level (not market level) very early on (p. 7).
[d] Is careful to define market surpluses as summations of MB and MC over quantities.

can label them MC and MB when contextually appropriate rather than continuing to label them S and D. I emphasize to my students the importance of first determining, for a single unit of the good, the vertical distances that correspond to the concept under examination. Only after having ascertained those distances should they add them together (i.e., shade them in) until they get to the relevant quantity. I have found that students who master this way of thinking are much less likely to go wrong, and they end up with a strong understanding of economic concepts and their various portrayals in verbal, algebraic, and graphical forms.

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Case Studies

Occupational Health and Safety Issues at Agribusiness Retailers

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JEL Codes: I1, L1, Q1, Q13
Keywords: Agribusiness, consolidation, cooperatives, health, safety

Abstract
This case explores efforts to improve occupational health and safety at RRV Cooperative, a fictional agricultural cooperative located in the upper Midwest. Students are introduced to the operations of farm supply and grain marketing cooperatives and to fundamental concepts in occupational health and safety. Students are asked to analyze data and consider the challenges in changing personal and group habits. Background information presented in this case offers additional teaching opportunities regarding trends in the farm supply and grain marketing industry and U.S. production agriculture.

1. Introduction

The light in Martha Giefer's office was the last one on at RRV Cooperative (RRVC) as day turned to night in July 2016. Martha was hired as RRVC's health and safety director in 2015. In her first year on the job, Martha developed several new projects to improve the cooperative's occupational health and safety. She also inherited a variety of ongoing projects, including an occupational health and safety study conducted by researchers at a land grant university. The university researchers collected data from RRVC and other agricultural cooperatives from 2012 to 2015, so much of the project was completed before Martha's time at RRVC. Nevertheless, the results from that survey, which sat on Martha's desk in a packet entitled "Occupational Health and Safety Survey Results," were the reason for the late night at the office.

Albert Johansen, the long-time general manager at RRVC, hired Martha to be the cooperative's first full-time health and safety director. RRVC is a farm supply and grain marketing cooperative located in eastern North Dakota. The cooperative's business lines include agronomy sales and service, feed production and sales, grain marketing and storage, refined fuels and propane delivery, and convenience stores. Martha applied for her current position at RRVC because the job description interested her and the cooperative was a critical business in her community. A few months after accepting her position at RRVC, Martha attended an occupational health and safety conference at which a university researcher showed data from one of the eight centers funded by Congress to work on health and safety issues. Additional presentations at the conference shared research from two dissertations in applied economics at the state university. Martha appreciated that some new research was focusing on agribusiness retailers such as agricultural cooperatives. Nevertheless, Martha believed that health and safety issues at agribusiness retailers received too little attention compared with similar issues faced by farm workers.

Like her peers at other firms, Martha designs educational and training programs for employees, implements health and safety policies, and completes compliance and regulatory paperwork. She also recommends investments in safety equipment or materials. More generally, Martha was hired to elevate RRVC's safety culture. Safety culture is a major topic among occupational health and safety professionals. Turner et al. (1989) contend that safety culture includes beliefs, attitudes, and practices that promote occupational health and safety. Safety culture may be defined by employee empowerment, which exists when "employees have a substantial voice in safety decisions, have the leverage to initiate and achieve safety improvements, hold themselves and others accountable for their actions, and take pride in the safety record of their organization" (Wiegmann et al. 2004, 127).

As Martha packed up to head home, she was still seeking answers regarding the survey's results. A few weeks prior, Martha agreed to summarize the survey's findings and make recommendations for future health and safety investments at RRVC's next board meeting. But as she exited the building, Martha was still trying to determine whether the report on her desk really mattered and how it could be used to improve safety culture and RRVC's bottom line. In the morning, she would review the results of the occupational health and safety survey with Albert and then participate in a conference call with the research team. After the call, Martha and Albert planned to discuss initial steps for improving occupational health and safety at RRVC. Martha hoped the next day's activities would help her to:

1. Understand the broad industry trends in the farm supply and grain marketing industries that have changed agriculture and how these changes have increased the need for education and training on occupational health and safety.
2. Differentiate between definitions and measures of safety culture and safety climate.
3. Construct occupational health and safety goals that are measurable and representative of a strategic plan.

Martha believed that achieving these objectives would improve her performance as RRVC's health and safety director and thereby move the entire cooperative in a positive direction.

2. Overview of Agricultural Cooperatives

Cooperatives exist in many agricultural and consumer industries (Boland 2018). Although cooperatives may vary widely, they share several unique characteristics related to the users of the business's goods or services. First, cooperatives are owned by their users, meaning that the users supply financial capital to the cooperative and are entitled to a share of the cooperative's profits. Cooperatives are also controlled by their users, meaning that the users elect directors to oversee the business. Finally, cooperatives are designed to benefit their users, meaning that the goods or services provided by the cooperative are beneficial to the users and that cooperatives should redistribute their profits based on use. In fact, cooperatives are referred to as participatory organizations because the more a customer participates in the business, the more benefits that customer receives.

Oftentimes, cooperatives provide goods or services that would otherwise be unavailable at a reasonable cost. This is true of many agricultural cooperatives, which generally operate in rural areas that may be overlooked by other businesses. Agricultural cooperatives also offer some market power to farm producers in an oligopsonic industry in which buyers are relatively large in size and small in number (Sexton 1986). Agricultural cooperatives include farm supply cooperatives, service cooperatives, and marketing cooperatives. Supply cooperatives offer farm inputs such as fertilizer, seed, feed, chemicals, and fuel. Service cooperatives may provide livestock shipping or grain storage. Marketing cooperatives sell users' agricultural production. Many agricultural cooperatives serve several of these functions and are therefore diversified businesses. In addition to core business lines like input supply and grain storage or handling, many agricultural cooperatives have additional non-agricultural business lines, including convenience stores, restaurants, or repair shops. Agricultural cooperatives are particularly common in the upper Midwest. In 2016, Minnesota, North Dakota, and Wisconsin ranked among the four states with the most agricultural cooperative headquarters (U.S. Department of Agriculture, Rural Development 2017).

3. The Regional Agricultural Economy

Martha grew up on a farm located on the eastern edge of RRVC's territory. Like many farms in that area in the early 1970s, her family's farm included a small beef feedlot, small grains such as hard red spring wheat and barley, and occasionally sunflowers or dry edible beans. Before Martha was born, her grandfather operated a dairy farm on the land. The crops traditionally planted on Martha's farm required relatively few crop inputs and generated small yields. As a result, RRVC and other area cooperatives did not need large agronomy or grain storage capabilities.

Production patterns in RRVC's area began to change in the early 1990s. During that time, Martha remembers her parents discussing planting soybeans for the first time. Several years later, her parents began planting corn. Martha's college agricultural policy instructor had talked about the "Freedom to Farm" U.S. Farm Bill in 1996. She remembers the instructor discussing likely changes to cropping patterns in the Red River Valley of northwest Minnesota and eastern North Dakota.

Since then, large-scale changes in the region's cropping patterns have occurred. Spring wheat, which was the primary crop in the region for decades, is now grown on fewer acres while corn and soybeans have surged in popularity. In North Dakota's Cass County, which sits in the heart of the Red River Valley, spring wheat acreage decreased by roughly 75 percent during the past two decades (U.S. Department of Agriculture, National Agricultural Statistics Service 2019). Corn yields per acre are several times those of small grains and require much greater volumes of crop inputs, especially nitrogen fertilizer. In addition, farming changed as new planting and harvesting equipment was needed to produce corn and soybeans. Because these crops have relatively narrow planting and harvesting windows, their production presented challenges to existing facilities and operations (Bechdol et al. 2010; Beddow and Pardey 2015). Those challenges spurred advancements in genetics, yield, and planting density that enabled farmers to work faster and operate more acres (Pardey and Wright 2003). Thus, farm sizes increased significantly.

The aforementioned changes had implications for RRVC, which is owned by area farmers. The agronomy and grain assets that RRVC owned in the 1990s were much too small for the demands of its territory's new cropping patterns. Consequently, from 2000 to 2010, RRVC experienced its biggest-ever capital asset expansion. Over the same period, RRVC consolidated with three other cooperatives at the same level of the agricultural supply chain, resulting in RRVC's horizontal expansion. The most recent consolidation occurred in 2013, when RRVC expanded its operations to 22 business locations with 250 employees through a merger with Northern Valley Cooperative. The merger with Northern Valley was a major reason for RRVC's interest in the occupational health and safety survey.

Similar changes have occurred elsewhere as the agricultural cooperative industry has evolved. Specifically, consolidation has reduced the number of agricultural cooperatives while business volume has increased. These trends are depicted in Figure 1. Consolidation among agricultural cooperatives mirrors increasing farm sizes and the emergence of large multinational agribusinesses through mergers and acquisitions among agricultural chemical and seed companies (MacDonald et al. 2018). Although business

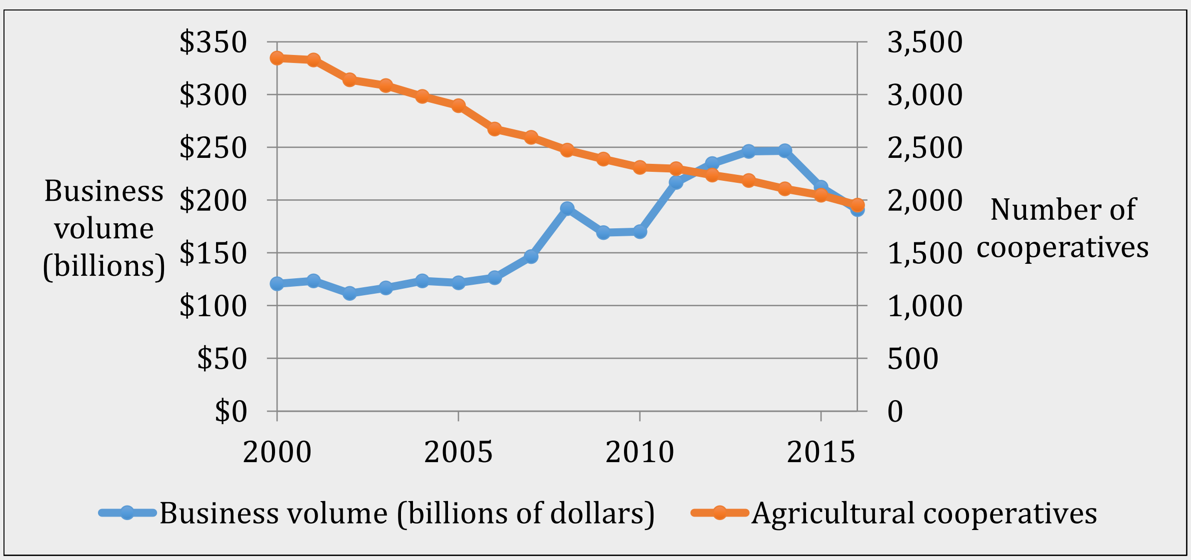

Figure 1. U.S. Agricultural Cooperatives and Agricultural Cooperative Business Volume

Source: U.S. Department of Agriculture, Rural Development (2017).

volume is partially driven by variable commodity prices, many agricultural cooperatives are handling more bushels of crop production than ever.

4. Health and Safety Challenges at Agricultural Cooperatives

The varied business lines at agricultural cooperatives create an array of unique health and safety challenges (Risch et al. 2014). Employees must handle and apply dangerous products like anhydrous ammonia fertilizer. Grain facilities expose employees to the dangers of grain dust explosions and grain engulfment. Large machinery, dangerous driving conditions, and many other hazards are also present at agricultural cooperatives. A recent four-year survey of 15 agricultural cooperatives reveals an average annual total recordable case incidence rate of 6.3 (Hanson 2016).[1] Table 1 shows that this incidence rate compares unfavorably with that of other industries and is roughly double the incidence rate for U.S. private industry.

Industry and employee characteristics pose additional health and safety challenges for agricultural cooperatives. For many cooperatives, consolidation has increased both the number of business locations and the geographic distance between them. As a result, maintaining stringent and uniform health and safety standards may be increasingly difficult for managers and health and safety personnel with cooperative-wide responsibilities. Post–merger employee onboarding may also be a challenge.

Increased business volumes at agricultural cooperatives are a particular challenge because the industry's workforce includes many older employees (Hanson 2016). Older employees may have established poor safety habits over years on the job. Older employees may also have relatively less physical resistance to injury. Many agricultural cooperative employees grew up working on farms or continue to work on farms seasonally or part time. Farms are notoriously dangerous workplaces where unsafe behaviors are often engrained in workers from a young age (Shortall et al. 2019). The average employee age at many agricultural cooperatives is relatively high, which implies that many new hires will be needed in coming years. This generational transition presents an opportunity for improving safety culture and performance while also raising concerns about lost institutional health and safety knowledge.

5. Economic Motivations for Occupational Health and Safety

There are many motivations for improving health and safety at agricultural cooperatives. An employee's desire to maintain quality of life and protect co-workers is the most basic motivation for health and safety. However, a recent survey of agricultural cooperative health and safety directors indicates that business concerns are also on the mind of safety-conscious managers (Hanson 2018). Financial arguments may influence managers who are accustomed to thinking on those terms (Adams 2002). Indeed, experience-rated insurance premia, lawsuits from injured employees, and regulatory fines damage a business's bottom

Table 1. Incidence Rates at Agricultural Cooperatives Versus Related Industries

Industry (NAICS code)[a]	TRC incidence rate[b]
Surveyed cooperatives	6.3
Private industry	2.8
Crop production (111)	5.6
Farm product warehousing and storage (49313)	2.4

Sources: Hanson (2016); U.S. Department of Labor, Bureau of Labor Statistics (2018).
[a] NAICS is the North American Industrial Classification System.
[b] Incidence rates are calculated as (injury and illness cases x 200,000) ÷ total hours worked, representing injuries and illnesses per 100 full time workers. BLS statistics represent 2016 data.

[1] Total recordable cases are all occupational injuries and illnesses that must be recorded for Occupational Safety and Health Administration (OSHA) purposes.

line. Work stoppages due to injuries and illnesses and the use of replacement or retrained workers may also harm a business's efficiency. Lastly, it may be difficult for a business with a poor health and safety reputation to attract and retain strong employees, which is particularly problematic in thin rural labor markets.

6. Overview of RRVC's Occupational Health and Safety Programs

Making RRVC more proactive on matters of occupational health and safety was a major goal for Martha. She instituted a system for anonymously submitting health and safety concerns and increased the frequency of safety inspections performed by herself and location managers. In accordance with "Right-to-Know" laws, Martha also presented information about dangerous chemicals used at RRVC. Her highest-profile effort was leading monthly safety meetings to communicate new policies and explain the findings of safety investigations after workplace injuries, illnesses, or near-misses.

7. Key Questions

Martha came into the office early the next morning to review the survey results before the conference call. The university research team that wrote the report had collaborated with 14 other agricultural cooperatives over a four-year period, from 2012 to 2015. Martha's predecessor, who did not have full-time health and safety responsibilities due to RRVC's smaller size at the time, had enrolled RRVC in the survey prior to his retirement. The researchers collected injury and illness data from RRVC each year from 2012 to 2015. In addition, RRVC employees completed a written survey in 2014. Martha was told of RRVC's survey participation during her hiring process, but she had not thought much about it after she provided injury and illness data to the research team during her first year on the job.

After inquiring about the health and safety survey's genesis, Martha discovered that a number of cooperatives like RRVC participated in long-running roundtables for chief executive officer (CEO) or chief financial officer (CFO) education. In 2010, one roundtable of farm supply and grain marketing cooperative CEOs invited an occupational health and safety speaker from DuPont to a meeting. The CEOs were interested in additional information on occupational health and safety, which led to the creation of a survey and a university-led research project on the topic.

The survey was designed to benchmark the cooperatives against one another and generate a written summary of the safety culture for each cooperative using a scale of zero (poor culture) to 100 (excellent culture). To ascertain the most basic measure of safety culture, the survey asked respondents to rate their empowerment to take actions that prevent injuries to themselves and their co-workers. As she read the report, Martha realized that the response rate had been almost 100 percent for many of the cooperatives. The survey results were broken out by business line and location as well as summarized for the entire cooperative.

Martha wrote down a series of questions to ask on the upcoming conference call. As she reflected on the results, Martha was disappointed that RRVC had received relatively low scores. Moreover, she knew that RRVC's directors would ask her difficult questions at the next board meeting. She wanted to be prepared to answer their questions. Martha also wanted to use the board meeting to propose a strategic vision for occupational health and safety at RRVC. Part of that vision included setting appropriate goals for the next three years. The questions on Martha's notepad were:

1. Why should our board of directors be concerned with occupational health and safety now and in the future? Which industry characteristics and trends are most important to this discussion?
2. What is the difference between safety climate and safety culture? How can these terms be used to frame what we can measure and what we want to measure?
3. Given that the mean score for all of the cooperatives was 72, with a standard deviation of 6.5 and a range of 63 to 84, what does RRVC's overall safety score of 63 signify? Do any important patterns emerge from the survey results and injury and illness data?

4. Where should RRVC's future health and safety investments be targeted? How will the effectiveness of those investments be measured? What is the relevance of causation and correlation to these efforts?

As Martha wrote down the last of these questions, she heard a knock on the door. Albert entered and asked, "Are we ready for the conference call?"

Martha responded, "I guess I am as ready as I can be. I spent some time going over the results last night. Since we have some time before the conference call, let me explain the key points as I see them." Martha went through her notes with Albert and asked for his thoughts about the four-year research project because she was not an employee when the project first started. He explained that one of his main takeaways from the educational programs was that all accidents can be prevented if the root causes of accidents are identified. Another takeaway, one underscored by injury and illness data, was that cooperative employees working with farmers had more reportable incidents than the farmers. That finding led Albert to enlist Martha's help in visiting customers' farms to improve health and safety. Thus far, RVVC had worked with 12 farms to reduce health and safety hazards relevant to both farm workers and cooperative employees. As a result, several farms had placed concrete in slippery areas, made it easier for large equipment to enter and exit a field, or engaged in other types of improvements.

Albert mentioned that education and awareness are critical for occupational health and safety, which is why he adopted the strategy, used by many senior leaders, of starting each meeting or conference call with a safety tip or discussion. RRVC's increased emphasis on health and safety resulted in the hiring of Martha and budgeting for increased annual expenditures for educational programs, which was not an easy task in an agricultural economy with little margin for such programs. But Albert was able to get buy-in from RRVC's directors by explaining how health and safety improvements could help RRVC's bottom line. Furthermore, Albert explained that "it was just the right thing to do."

Albert was unsure about what would emerge in the survey results. The survey was completed in 2014, roughly one year before Martha was hired. He knew it would take time to see results because safety improvements are a continuous process. A follow-up survey was scheduled to be implemented in about three years, or roughly five years after the original survey. Albert believed that the cooperative's safety culture was improving. However, he also acknowledged that safety culture was uneven across RRVC's locations, leaving much room for improvement. As Martha's computer alarm went off, Martha and Albert knew it was time to join the call.

8. Analyzing the Results

After the call participants were introduced, the university professor and doctoral student went through each survey question and discussed the main implications. The questions were aggregated into three main categories: leadership and support, empowerment and action, and accountability and responsiveness. Survey results were also summarized by job category (managers, supervisors, hourly employees, professionals), business location (for confidentiality purposes, a location needed five or more responses for its results to be reported), employee age (ten-year increments starting at age 20), and business line (agronomy, energy, feed, grain, office, retail, transportation). The results were benchmarked against the other cooperatives in the survey. Finally, any written comments from the surveys were discussed.

Martha wrote down the key points as she and Albert listened. After 20 minutes, the speakerphone went silent. It was time for questions. "If I understand you correctly, the overall set of cooperatives had a relatively low score," began Martha. "So, we all have room to improve. But RRVC has more room for improvement than most." There was agreement on that issue. RVVC had not "failed," but rather its results were low and suggestive that improvement was needed.

The conversation then shifted to particular areas in which RRVC could improve. It was clear from the written comments that the employees believed that all of the attention on health and safety was a short-term issue. "We have talked about safety during all of my 40 years as an employee," one respondent wrote, "but when it is planting or harvest season, it is 'all hands on deck,' and safety goes out the window as we work all hours of the day to help our members." The call participants agreed that leadership from the CEO would be needed to change the culture. In addition, employees recognized that RRVC had increased its investment in occupational health and safety. Although employees recognized some change as a result, surveys revealed that the employees were generally less positive than supervisors about RRVC's safety culture and the effectiveness of the cooperative's leadership in promoting occupational health and safety.

During the conference call and in the survey report, the research team talked about "safety climate." Martha asked the university professor and doctoral student about this terminology. According to the researchers, "Safety culture is an all-encompassing term for values and beliefs that may be evolving everyday. Therefore, it is difficult to capture culture perfectly through a questionnaire. Instead, it may be more accurate to say that those questions describe a firm's moment-in-time safety climate."

The discussion of safety climate and culture led to talk about the connection between survey results and safety outcomes, such as injury and illness frequency and severity. The researchers noted that they wanted to be careful in making sure any relationship between these variables was causal and not simply a correlation. According to the professor on the call, "Just because two things happen at the same time does not mean that one causes the other. If we want to improve safety, we want to focus on things that actually change safety outcomes." The professor mentioned that it is easy to be fooled by reverse causality or endogeneity when examining a relationship between two variables like safety culture and safety outcomes. The researchers promised to send more information to explain these statistical concepts. As the call concluded, Martha looked down at her full notebook and began considering the future of RRVC's occupational health and safety programs.

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Teaching and Education Commentaries

Let's take a moment to celebrate great teaching!

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JEL Codes: A22, Q0
Keywords: AAEA, archival review, biases, teaching awards

Abstract
This commentary uses the history of the teaching awards program of the Agricultural and Applied Economics Association (AAEA) to examine the AAEA's commitment to the teaching mission of universities with undergraduate programs in agricultural and applied economics. Through an archival review of AAEA historical documents, it describes an evolving commitment. It also identifies, from the author's personal perspective, several awards program benefits and raises several concerns about potential biases in the selection of awardees. The commentary is, above all, a tribute to teaching and to AAEA teaching award recipients—past and future.

The Agricultural and Applied Economics Association has a rich and wonderful decades-long history of recognizing outstanding teaching. This commentary is an attempt to document this history and, in the process, to identify possible means for enriching the AAEA's institutional capacity to acknowledge and celebrate great teaching for decades to come.

The 2018 annual meetings of the AAEA marked the 51st year that the association has presented teaching awards to its members. The first recipient of an AAEA teaching award was Raymond R. Beneke, who was recognized at the 1968 annual meeting. Over time, the association began giving multiple awards, distinguishing recipients by their teaching experience—either early career (fewer than 10 years) or later career (10 or more years)—and their students' academic level—undergraduate or graduate.

Table 1 presents a complete list of award winners, whose names were culled in part from archival records maintained by the AAEA's Teaching, Learning and Communications (TLC) Section. These records date from 1997 and are accessible on the AAEA website (www.aaea.org /membership/sections/tlc/aaea-teaching-award-winners). Pre-1997 winners were identified through examination of the *American Journal of Agricultural Economics/Journal of Farm Economics*, which for many years published committee reports, and the minutes of association annual business meetings and board meetings. These records shed light on the association's evolving commitment to the teaching mission. The Awards Committee's annual reports to the AAEA Board are particularly rich in detail. Additional insights about the association's awards history are captured in Paul Barkley's *A Centennial History of the AAEA* (Barkley 2010). Readers should note that these archival records capture an amazing amount of minutia, and that minutia is a testament to the incredible commitment and service many past members of the AAEA have dedicated to furthering the vitality and viability of the organization.

The AFEA (as the AAEA was formerly known) initiated an awards program in the early 1940s, but those efforts did not include any consideration about teaching. As Barkley (2010) notes the idea for establishing an award for outstanding undergraduate teaching was student driven. Student ag econ clubs, which had begun to form on campuses in the post WW-II era, were woven into the broader context of the national association by the late 1950s, including student-organized programming at the annual meetings and a national student organization that was affiliated with the AFAE. In 1962, student members proposed to the AFEA Executive Committee that the association should annually name and award an "outstanding undergraduate teacher in agricultural economics," which ultimately led to the first award in 1968.

These students also proposed that the association organize a workshop for its members to improve the quality of undergraduate teaching in agricultural economics. The result was two national workshops, one held in 1963, which had 84 faculty participants, and one in 1966, which had 90 faculty participants (Barkley 2010). These workshops represent the first recorded efforts by the association to emphasize the teaching mission in the association's first 50-plus years of existence.

The development of the teaching award and the two national teaching workshops were early indicators of a fundamental shift in the association's collective perspective about teaching. John Sjo (1974) documented this shift in his committee report to the AAEA Board, "The AAEA: Its Responsibility for Instructional Leadership."" This report begins quite starkly, "In the 54 years since its founding in 1919, the American Agricultural Economics Association has been an association primarily of researchers, not teachers" (p. 436). Later in the same report, Sjo notes, "Undergraduate instruction has not been viewed among agricultural economists as their most prestigious activity" (p. 438). Sjo concludes, "Historically the role of the Association in undergraduate instruction has been one of neglect" (p. 439). In short, the teaching mission was not one of the historic priorities of the association.

A complete read of Sjo's report documents the numerous steps the AAEA leadership took during the 1960s and early 1970s to elevate the association's engagement in the teaching mission. These steps included establishment of the teaching award and a commitment to include program content about teaching at the association's annual meetings.

Since the 1970s, the AAEA's commitment to the teaching mission has incrementally grown and matured. Additional workshops and symposia have continued, the teaching award has been refined to include at first two and then three categories of awardees per year, and in 2002, the AAEA's Teaching, Learning, and Communications (TLC) Section was established. The section has institutionalized teaching-focused programming at the annual meetings through its track sessions.

Table 1 lists all those who have been awarded for great teaching. And it leads me to observe how, in unexpected ways, my personal story is woven within the association's teaching award history. As an undergraduate majoring in agricultural economics at Kansas State University in the early 1980s, I enrolled in Bryan Schurle's Principles of Agricultural Economics course. To this day, I remember Bryan's lectures and more importantly, his passion, his dedication to his craft, and his sincere interest in his students' learning. He made the course material relevant, compelling, and, at times, even fun. That course, more than any other, set me on my professional career path as an agricultural economist. Bryan Schurle received the AAEA Undergraduate Teaching Award in 1987.

At the time I was an undergraduate, the Kansas State Agricultural Economics Department's policy for undergraduate advising was to assign every student in the major to a faculty member, who was responsible for student advising and mentoring. John Sjo was my advisor, and he was the first person to suggest to me that I should consider graduate studies in agricultural economics. He was the mentor who made the difference early in my professional development, because he took the time to be personally invested in my future. He saw in me potential that I did not personally recognize, and he helped me appreciate the scope and breadth of possibilities that my future could entail. Dr. Sjo helped me see beyond the world I knew. John Sjo received the AAEA Undergraduate Teaching Award in 1973.

I mention these two anecdotes of my personal history to highlight examples that ever so slightly pull back the veil of mystery familiar to anyone who teaches undergraduate students. It is so easy to ask, "Am I really making a difference?" Or worse, if it has been one of those days, perhaps after grading a midterm exam that did not go particularly well, you might ask, "Why do I even try?" My retort: Dr. Schurle and, if he were still alive, Dr. Sjo would be hard pressed to remember me as one of their former undergraduate students in the early 1980s. Yet, I remember them. The echoes of teaching excellence are slow to reverberate and often go unheard, but I am convinced that no matter how muted the evidence, great teaching and great teachers change lives and are powerful forces for progress in our world.

Table 1 AAEA Teaching Award Winners (Names and Institutions), 1968 to 2018

Year	Undergraduate Teaching Award		Graduate Teaching Award
	< 10 Years' Experience	10+ Years' Experience	
2018	Sierra Howry University of Wisconsin, River Falls	James Sterns Oregon State University	Gerald Shively Purdue University
2017	Alex Shanoyan Kansas State University	Chris Barrett Cornell University	William Wilson North Dakota State University
2016	Jason Bergtold Kansas State University	Andrew Barkley Kansas State University	Philip Garcia University of Illinois
2015	Nicholas Paulson University of Illinois	W. Marshall Frasier Colorado State University	Richard Sexton University of California, Davis
2014	Brian Briggeman Kansas State University	Cheryl Wachenheim North Dakota State University	Richard Just University of Maryland
2013	Shannon Ferrell Oklahoma State University	Ron Hansen University of Nebraska	Wally Tyner Purdue University
2012	Michael A. Gunderson University of Florida	Stephen Devadoss University of Idaho	Terry Roe University of Minnesota
2011	Scott Downey Purdue University	Frank Dooley Purdue University	Stephen Devadoss University of Idaho
2010	Hayley Chouinard Washington State University	Kerry K. Litzenberg Texas A&M University	Shida Henneberry Oklahoma State University
2009	James A. Sterns University of Florida	Michael A. Boland Kansas State University	Kenneth A. Foster Purdue University
2008	F. Bailey Norwood Oklahoma State University	James B. Kliebenstein Iowa State University	Francis M. Epplin Oklahoma State University
2007	Darren Hudson Mississippi State University	Dixie W. Reaves Virginia Polytechnic Institute	Michael E. Wetzstein University of Georgia
2006	Christine Wilson Purdue University	Donald Liu University of Minnesota	Richard Boisvert Cornell University
2005	Lisa House University of Florida	Paul Wilson University of Arizona	James Richardson Texas A&M University
2004	Marshall Frasier Colorado State University	Daniel Tilley Oklahoma State University	B. Wade Brorsen Oklahoma State University
2003	Allen F. Wysocki University of Florida	James Beierlein Pennsylvania State University	Paul Preckel Purdue University
2002	Cynda Clary New Mexico State University	Ronald Deiter Iowa State University	Allen M. Featherstone Kansas State University

Table 1 Continued.

Year	Undergraduate Teaching Award		Graduate Teaching Award
	< 10 Years' Experience	10+ Years' Experience	
2001	Michael A. Boland Kansas State University	Jay T. Akridge Purdue University	Ron Mittelhammer Washington State University
2000	Frank Dooley Purdue University	Raymond Folwell Washington State University	Jeffrey Williams University of California, Davis
1999	Mary A. Marchant University of Kentucky	Carl R. Zulauf The Ohio State University	Oral Capps, Jr. Texas A&M University
1998	Patrick J. Byrne University of Florida	Gary F. Fairchild University of Florida	James E. Wilen University of California, Davis
1997	Lois Schertz Willett Cornell University	Michael E. Wetzstein University of Georgia	Jean-Paul Chavas University of Wisconsin, Madison
1996	E. Jane Luzar Louisiana State University	Steven Sonka University of Illinois	Walter Thurman North Carolina State University
1995	Andrew Barkley Kansas State University	David Kohl Virginia Polytechnic Institute	
1994	Kim Harris Southern Illinois University	Fred White University of Georgia	
1993	Edward McLaughlin Cornell University	John Kadlec Purdue University	
1992	Stephen Turner University of Georgia	Stephen Erickson Purdue University	
1991	Carl Zulauf Ohio State University	Wayne Purcell Virginia Polytechnic Institute	
1990	Dorothy Comer University of Florida	Bernard Erven Ohio State University	
1989	Jill Sovocool Findeis Pennsylvania State University	Joseph Uhl Purdue University	
1988	Michael Hudson University of Illinois	Josef Broder University of Georgia	
1987	Bryan Schurle Kansas State University	Lawrence Bohl Purdue University	
1986	James Russell Oklahoma State University	Stephen Matthews University of Missouri	
1985	Kerry Litzenberg Texas A&M University	John Penson, Jr. Texas A&M University	
1984	David Kohl Virginia Polytechnic Institute	Robert Oehrtman Oklahoma State University	

Table 1 Continued.

Year	Undergraduate Teaching Award: < 10 Years' Experience	Undergraduate Teaching Award: 10+ Years' Experience	Graduate Teaching Award
1983	Josef Broder University of Georgia	H. Evan Drummond University of Florida	
1982	Joe Davis University of Kentucky	Richard Aplin Cornell University	
1981	Kenneth Casavant Washington State University	W. David Downey Purdue University	
1980	Ronald Hanson University of Nebraska	Robert Taylor Purdue University	
1975	Lawrence Bohl Purdue University	Kenneth Boggs University of Missouri	
1974	Glenn Himes Ohio State University	Lester Manderscheid Michigan State University	
1973	Wayne Purcell Oklahoma State University	John Sjo Kansas State University	
1972	W. David Downey Purdue University	R.G.F. Spitze University of Illinois	
1971	John Goodwin Oklahoma State University	Lawrence Darrah Cornell University	
1970	Robert W. Taylor Purdue University		
1969	Albert H. Harrington Washington State University		
1968	Raymond R. Beneke Iowa State University		

Note: Prior to 1996, the AAEA had no award recognizing distinguished graduate teaching. Prior to 1971, the AAEA had only one award; it recognized distinguished undergraduate teaching.
Sources: Agricultural and Applied Economics Association, Teaching, Learning, and Communication Section, https://www.aaea.org/membership/sections/tlc/aaea-teaching-award-winners; Awards Committee Reports, *American Journal of Agricultural Economics*, 1968–1996 (December issues)

Compilation of Table 1 reinforced my perception that there are some truly great teachers in our profession. Two of them have been recognized by the AAEA at both the undergraduate and graduate level: Michael Wetzstein, who received the undergraduate teaching award in 1997 and the graduate teaching award in 2007, and Stephen Devadoss, who received the undergraduate teaching award in 2012 and the graduate teaching award in 2011. When asked, Michael Wetzstein admitted that the approaches for teaching undergraduates and graduate students are fundamentally different. With the former, the focus is on motivation and providing content in an array of formats (i.e., graphs, mathematics, numerical examples, real-world applications, and so on); with the latter, the focus is on theory and content that are just plain hard to learn without help (i.e., the intuition, the grind, and the poetry of economics).

Table 1 also documents the sustained success of awardees who have been recognized both early and later in their careers. Thirteen individuals have been awarded the AAEA Distinguished Undergraduate Teaching Award twice, once for the "Under 10 years of teaching" and once for the "More than 10 years teaching" awards. These are

- W. David Downey, Purdue University (1972, 1981)
- Wayne Purcell, Oklahoma State University/Virginia Polytechnic Institute (1973, 1991)
- Lawrence Bohl, Purdue University (1975, 1987)
- Ronald Hanson, University of Nebraska (1980, 2013)
- Josef Broder, University of Georgia (1983, 1988)
- David Kohl, Virginia Polytechnic Institute (1984, 1995)
- Kerry Litzenberg, Texas A&M (1985, 2010)
- Carl Zulauf, Ohio State University (1991, 1999)
- Andrew Barkley, Kansas State University (1995, 2016)
- Frank Dooley, Purdue University (2000, 2011)
- Michael Boland, Kansas State University (2001, 2009)
- Marshall Frasier, Colorado State University (2004, 2015)
- James Sterns, University of Florida/Oregon State University (2009, 2018)

The awardees in Table 1 are also awardees of other organizations and agencies. Many of them are among the 60 academics recognized by the Western Agricultural Economics Association for their teaching excellence (WAEA 1982–2009). Nearly a third of the 40 recipients of the Southern Agricultural Economics Association's "Outstanding Teaching of a Course" award are also listed in Table 1 (SAEA 2019). Nineteen of the AAEA awardees have been recognized at the regional or national level by the United States Department of Agriculture's National Award Program for Excellence in College and University Teaching in Food and Agricultural Sciences (USDA 2019a; USDA 2019b).

Table 1 also raises some personal concerns that I hope will be addressed by the AAEA leadership and by the membership as a whole. First, most of the awardees have been men. Of the 107 individuals that have been recognized for their teaching excellence, only 13 have been women. Second, the 107 awardees have been faculty members at just 32 universities. Although that number represents more than half of the 1862 Land Grants, none of the awardees have been faculty members at one of the nineteen 1890 Land Grants. None have been faculty members at one of the 32 tribal colleges and universities that have land grant status. Only two have been faculty members at one of the 58 institutions recognized by the Association of Public and Land-Grant Universities (APLU) as Non-Land Grant Colleges of Agriculture. Similalry, the majority of awardees of other agricultural associations and agencies have been male and employed at 1862 Land Grants.

To address concerns about potential inherent biases in the processes for acknowledging and awarding great teaching, the first step would be to document the empirical evidence, which this missive partial does. The second step would be to seek evidence of causality, and the third would be to raise awareness and prioritization, and then commitment to substantive action. All these tasks are well within our individual and collective means.

One of my former students inadvertently provided a wonderful summary of what it means to pursue great teaching. In describing her study abroad experience with a program that I had co-led, she said, "Maturity and stamina are vital. If you're unwilling to be wrong, don't bother going. It's exhilarating, transformative, and ridiculously fun." That description can just as easily apply to the pursuit of excellence in the classroom. Let's take a moment to celebrate that excellence!

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Teaching and Education Commentaries

Moneyball in the Academy: Whiffing on the Quality of Education?

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Abstract
In recent years, corporate-like resource management tools have become commonplace on many university campuses with the goal of improving economic efficiency at the organizational level. Administrative initiatives that calculate faculty and department value with a limited number of metrics jeopardize the relational and hence the learning environment of higher education, particularly at the undergraduate level. Mutual faculty-student engagement remains a critical component of a quality education.

Moneyball, using data analytics to forecast player performance and hence player value to a team, is now mainstream in professional team sports, particularly baseball (Lewis 2003).[1] Moneyball or sabermetrics-like tools have also invaded higher education in the form of resource allocation and data management systems (e.g. responsibility-centered management). Over the last decade, higher education invested millions of dollars on new software, consultants, administrators, and staff to make these systems operational. The implied goals of these systems are to minimize cost for a given level of education, maximize revenue per credit hour, and/or maximize credit hours. Generally, data-based decision making should be encouraged and expected in any organization; an exception occurs when data systems drive the learning process. Leroy Dubeck (1997) warned the academy over two decades ago that students can be disadvantaged in an academic environment where an implicit goal is to minimize cost per student without maintaining quality education (Deering and Sá 2018).[2]

State-supported universities experienced two decades of nearly annual budget cuts that accelerated at the onset of the Great Recession. Only 10–20 percent of many state universities' budgets now are state tax dollars. New and existing revenue sources expanded to keep our multimillion dollar educational "cities" in operation. Average college tuition increased by nearly 400 percent over the last two decades, twice the rate of inflation (Vedder 2019).[3] Students (sometimes seen as "students as ATMs") and the federal government paid an increasing share of efforts to maintain and expand our academic enterprises. In this fiscally challenging academic environment, moneyball has emerged as a prominent resource management tool for many universities.

Academic units, including colleges and departments, along with individual faculty members now see their academic value or performance measured by a select group of money-centric metrics: number of majors, class size, and indirect cost recovery from research projects. These metrics are continuing to play a more dominant role. As a result, student-recruiting efforts resemble Division I recruiting for college

[1] Remember the movie *Moneyball* (2011), starring Brad Pitt? Refresh your memory with one or more of the movie's film clips at www.youtube.com.
[2] Deering and Sá's recent evaluation complements and updates Dubeck's prophetic warning concerning responsibility-centered management.
[3] Beth Akers (Manhattan Institute), Preston Cooper (Forbes), Jason Delisle (National Affairs), and William Massy (American Enterprise Institute) are other examples of analysts who have written consistently over the last decade on the changing costs and benefits of higher education.

athletes with universities, colleges, and departments competing for larger student enrollments each year via amenities. Examples are luxury housing; entertaining classes; financial incentive "contracts" including diverse packages of scholarships, loans, grants, and work study; new senior administrative positions and recruitment programs to ensure we get "butts in the seats"; lower admission requirements; an ever increasing number of majors and classes to meet every student's interests; and more student support staff (Ginsburg 2013).[4] Departments do their best to keep their student majors in departmental courses where the department earns the student credit hours, not allowing their students to "escape" to a relevant course in another department. Poaching another department's majors goes on every day on our campuses.

Meanwhile, big-dollar researchers play the role of franchise academic players. Their successful federal and private grantsmanship is critical for overall team performance and reputation, particularly on the national and international stages. However, during private moments, research administrators will often confess that tuition dollars clearly subsidize research on nearly every state-supported campus.

Not surprisingly, many faculty dislike the sabermetric-like approach to productivity because the metrics reduce their professional value to the university to primarily two factors: (1) how many students they teach, and (2) how many grant dollars (with high levels of indirect cost recovery) they bring to the university. What about their research contributions? What about their value in the "locker room" as a team player? Incentivizing teaching larger and more classes or spending more hours in the laboratory thins the level of social capital in universities. This jeopardizes the quality of undergraduate education received by the majority of our students, particularly those who are at risk of not completing their degree (e.g. first-generation college students). So, has the on-field performance of our universities improved with these impersonal moneyball metrics? Are our young people now being better prepared for the personal, political, social, and economic realities of the twenty-first century?

Moneyball in the academy can whiff on improving the quality of higher education. I was once asked by a skeptical, high-level university administrator, in a disparagingly manner, "so what is a quality education anyway?" Well, a quality education happens when the passion and competence of the professor is combined with well-designed student-faculty and student-student interactions that prepare an engaged student for a productive and meaningful life. Unfortunately, moneyball in the academy can sacrifice the relational component of a quality education on the altar of the academy's corporatization and its ever-present cost-minimizing focus.

If you think about it, we have all had one or more key mentors in our academic lives who influenced our learning and career trajectories. These life-changing mentors may be a kindergarten teacher, a middle school science teacher, a high school math teacher, a coach, or a dynamic university professor: a person who knew your name, challenged and encouraged you, believed in you, and taught you life skills with hands-on learning experiences. They left their mark on you.

Unfortunately, our continued drive for even greater student numbers and class size jeopardizes the role these positive and critical learning relationships play between students and instructors. We quickly depersonalize undergraduate instruction as we direct students into larger classes and more online instruction largely to minimize cost and enhance revenue ("students have a dollar sign on their foreheads") but at a reduction, in most cases, in educational quality. Educational quality suffers with fewer, smaller face-to-face experiences where a student can apprentice in the subject matter under the instructor's watchful guidance.

Moneyball in the academy degrades an academic environment by not engaging the whole person, so the educational experience fails to become part of the student's identity. We are thinning rather than thickening the relational bonds in higher education when larger, "more efficient" classes substitute for small class experiences.

So how can the academy hit a home run by a return to emphasizing student development rather than student dollars in a moneyball environment? For starters, change the lineup. All PhDs on campus

[4] Benjamin Ginsberg (2013) provides a disturbing insider's analysis of the growing number of administrative and staff positions in U.S. universities.

should be expected to have the responsibility of teaching one, regularly scheduled three-unit undergraduate or graduate class each year. That's right, all classroom competent administrators below the Provost level should be actively engaged in teaching. The result: fewer unproductive meetings and programs, smaller classes because there are more teachers, and an improved, firsthand understanding of student learning issues by administrators who are not currently engaged in the classroom.

Second, adopt a small ball strategy where all student-friendly PhD-level instructors are encouraged (required?) to annually teach one 1-unit workshop or colloquium (15 to 20 students) on a disciplinary topic of their choice. All students would be encouraged, or possibly even required, to complete one of these workshops each academic year. The result: a thickening of the relational bond between students and faculty who know students' names.

Long term we should expect universities to (1) work on their farm system by formally training their future faculty members on the art and science of teaching, learning, and caring; and (2) provide the moneyball incentives in career development (promotion and tenure), which properly elevates and aligns student-faculty engagement with the research responsibilities of the organization.

All students matter; students matter most of all.

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