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Contents

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Research Article

How Do Students Allocate Their Time? An Application of Prospect Theory to Trade-offs between Time Spent to Improve GPA Versus Time Spent on Other Activities

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Keywords: Teaching and learning, prospect theory, choice experiment, university students

Abstract
We employ a choice experiment survey to elicit university students' preferences for grade point average (GPA) relative to time spent on various activities. Using expected utility and prospect theory approaches to analyze those preferences, we find statistically significant asymmetry between the desire to increase GPA and the desire to avoid a decrease in GPA. Surveyed students were loss averse regarding GPA: they would trade approximately 4.6 times as much free time to avoid losing a point in their semester GPA relative to time they are willing to give up to gain one additional point. This study contributes to the growing research regarding prospect theory by analyzing loss aversion in a novel context of students' time allocation.

1 Introduction

Most instructors view college success in terms of academic achievement, as measured by grade point average (GPA).[1] As a result, instructors use course grades and their impact on GPA as motivation to encourage students to perform well on assignments, prepare for exams, and meet course requirements. However, the university experience also involves social opportunities and pressures, extracurricular academic pursuits, employment, and recreational activities, all of which play a role in developing well-rounded students. Therefore, rational students will allocate their scarce time between efforts to improve GPA and other activities in a way that maximizes utility, given the constraints that they face (Kelley 1975; Ballard 2014). For each student, constraints and preferences will vary. For example, some students must work each week to pay for university expenses and housing. Other students might value the networking and social benefits offered by involvement in a fraternity or sorority. The economic approach to human behavior considers GPA to be just one of numerous rational ways to define university success.

Kelly (1975) postulated the reasons that students may have a disinterest in GPA level. He found some students are unmotivated by GPA changes because they view university as a "screening" output, the value of which is measured largely by the college degree earned. If so, a rational, utility-maximizing student might aim to achieve merely the minimum academic requirements for graduation. In this extreme case, minor increases in GPA do not increase utility because these increases do not affect the earning of a degree. If an institution requires a 2.0 GPA to grant a diploma, students who care only about earning a degree would achieve this goal with a 2.1 GPA just as they would with a 2.4 GPA.

[1] Throughout, we assume GPA to be measured on a 0 to 4 scale: A=4, B=3, C=2, D=1, F=0. Some U.S. universities calculate grades on the basis of plusses or minuses on letter grades, and some European universities use percentages instead of letter grades for courses. Because the research was conducted at Kansas State University, we assume students interpreted all questions in light of that university's policies.

To gauge the views of students surveyed in this research, we asked them to rank five university goals in order of importance: graduation, academic achievement, income after graduation, networking for the future, and social experiences. In general, survey results confirm that the findings of Kelley (1975) are a reasonable possibility. Figure 1 shows the relative importance of the goals. Academic achievement is third, and graduation is markedly more important than other goals. These results suggest that students' decisions are perhaps not as driven by GPA as one might think.

The complexity of students' decisions in broad behavioral economic research and the specific evidence that students in this study are perhaps more driven by graduating than by academic achievement motivate our research. Knowing how students value the trade-offs between time spent attempting to improve GPA versus time spent on other activities will provide instructors with a deeper understanding of students' choices and motivation. Furthermore, university leadership may use this knowledge to alter university offerings to better appeal to prospective students.

Important, existing literature has largely left students' time allocation decisions unaddressed. This study begins to fill this knowledge gap by using choice experiment analysis and a novel prospect theory (Tversky and Kahneman 1992), general application of which has been growing (Caputo, Lusk, and Nayga 2019). Furthermore, behavioral economics has spawned productive research to understand the complex educational decisions of students and policy makers (Koch, Nafziger, and Nielsen 2015). Students'

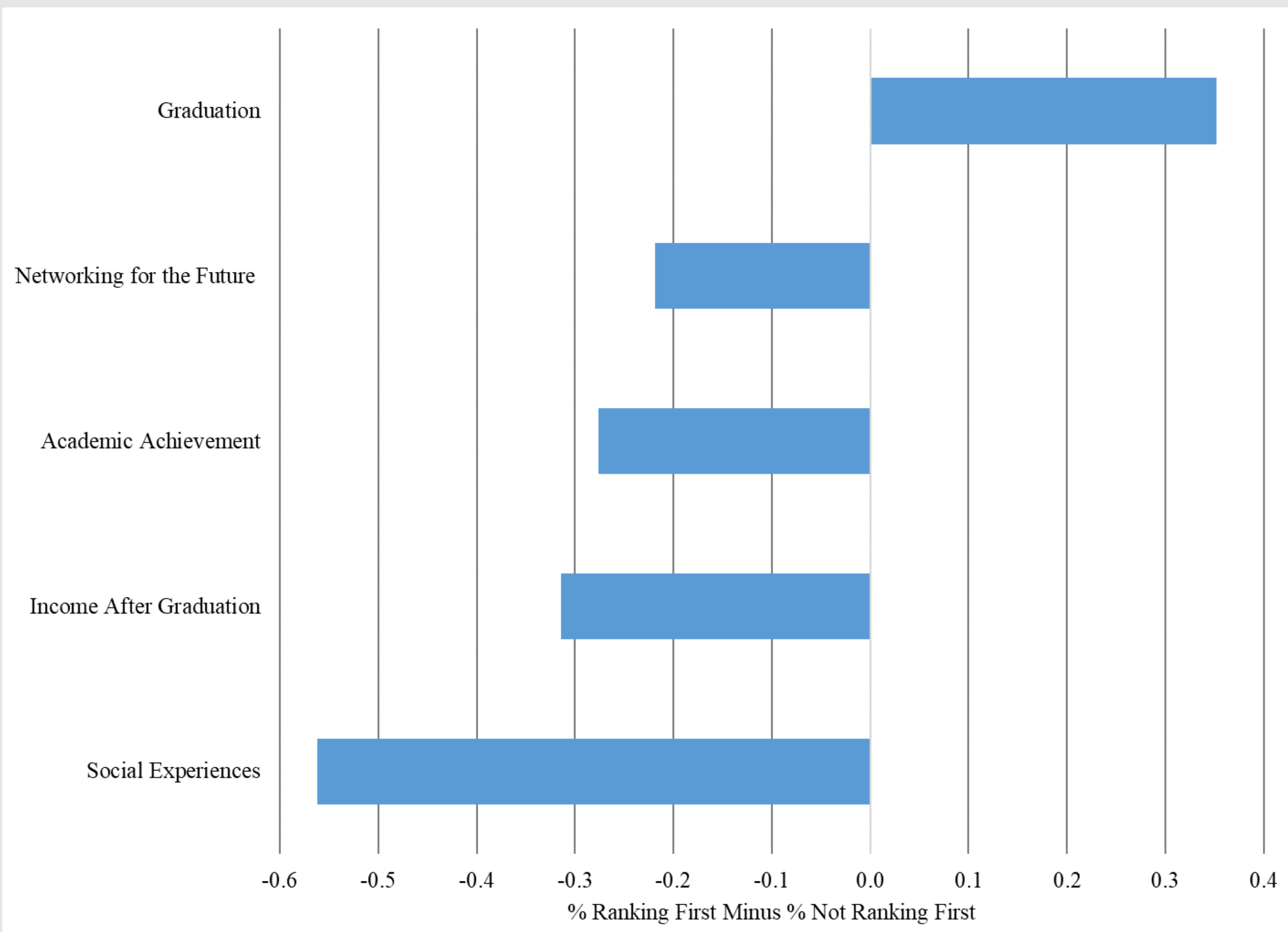

Figure 1. Relative Importance of University Goals

Note: Ranking is percent of times ranked first minus percent times ranked 2 to 5. Scale is bound -1 to 1. N=105.

decisions may be biased by seemingly small issues, such as the current weather during a campus visit (Simonsohn 2010). The increased use of behavioral economics to complement traditional economic analysis, in education and beyond, makes analysis of students' time allocation decisions timely. The choice experiment is novel in that we know of no other experiment that has measured trade-offs between GPA and time allocation. Allowing asymmetry between GPA gains and losses introduces prospect theory into the analysis.

The main objective of this research is to quantify the value that university students place on GPA relative to time spent on other activities. Specifically, we use choice experiments to elicit student trade-offs between time spent studying and time spent on other activities. We find that all students value an increase in GPA, but particularly students with a relatively high GPA. Time spent studying decreases utility, ceteris paribus, for students with relatively low GPAs. Among all offered activities, unstructured free time has the highest value. Finally, we find statistically significant asymmetry between the desire to increase GPA and the desire to avoid a decrease in GPA. Surveyed students would trade approximately 4.6 times as much free time to avoid losing a point in their semester GPA relative to time they are willing to give up to gain one additional point. This behavioral asymmetry is the major contribution of our research, and it has several implications for teaching and learning.

2 Student Time Allocation Background and Survey Design

The majority of empirical research on how university students allocate time is focused on class attendance, study time, or student effort (Schmidt 1983; Romer 1993; Devadoss and Foltz 1996; Bratti and Staffolani 2013; Krohn and O'Connor 2005). This body of research is enlightening in terms of conceptualizing and measuring the impact of attendance and study effort on student grades. A topic that has received less attention are the decisions of students concerning how to allocate their time. This study is the first to estimate and quantify students' perceived costs and benefits associated with time spent on a given activity. Some of the benefits might be related to improving GPA. However, some activities, such as networking or socializing, might offer long-term benefits but actually harm GPA in the short run. Likewise, some activities might be detrimental to GPA but offer short-term enjoyment to the student. In any case, an economically rational student would budget time accordingly and experience the resulting trade-offs.

When no market exists, economic research has increasingly relied on nonmarket valuation to estimate willingness to pay (Champ, Boyle, and Brown 2017). There have been many applications of such choice experiment frameworks in food and agriculture, including willingness of consumers to pay for specific traits of meat products (Lusk, Roosen, and Fox 2003), consumer preferences regarding meat labeling (Tonsor, Schroeder, and Lusk 2013), and livestock producer willingness to purchase feeder cattle and adopt feeding treatments in the face of uncertainty around pounds gained during feeding (Tonsor 2018). There are few applications of choice experiments to education, especially to elicit how students value academic achievement (i.e., GPA) relative to other attributes of the university experience. The application of choice experiment analysis provides a new perspective for the student choice literature and shows the ways that students think about increases and decreases in GPA.

In many choice experiments, participating subjects face a choice between goods with varying attributes and prices (Lusk et al. 2003; Tonsor , Schroeder, and Lusk 2013). By analyzing respondent choices over the various combinations of attributes and prices, a willingness to pay for those attributes can be estimated. In the case of student choice, there is no explicit cash price. Instead, students are asked to choose among alternatives with varying levels of GPA and weekly time commitments to various activities. Improved GPA is assumed to have some benefit for the student. This benefit could be a qualification for awards, signaling to potential employers, sense of personal accomplishment, or a proxy for attained education. Time may be spent in a way that directly influences GPA or not. In this way, the traditional trade-off between money and attribute levels becomes a trade-off between GPA level and time allocation.

On the basis of classroom pre-surveys, the authors' teaching experiences, and educational literature, we identified a group of broadly defined activities among which students allocate their weekly time. Table 1 shows the categories of time use and GPA. It includes the levels of each category (attribute) used in the choice experiment, as explained below. The included activities broadly cover how a student might spend time. "Studying" is included as a unique category to measure a student's effort to improve GPA. The other activities are not expected to increase GPA, but they could provide utility to the student. "Fraternity/Sorority/Club Activities" could offer memorable experiences and an opportunity to build social capital or social skills. "Fitness/Sports/Recreation Activities" offer a release of stress and an opportunity for personal accomplishment. However, it is also possible that fitness activities such as intramural sports, personal exercise, yoga, and related activities have a negative impact on utility for some students. "Unstructured Social Activity" offers the opportunity to be with others but has no long-term commitment, unlike "Fraternity/Sorority/Club Activities." Finally, on the basis of responses and comments we received in pre-testing for the survey, we included a completely unstructured time category: "Other Activities." An anonymous reviewer pointed out the conspicuous absence of work among the activities. Work is certainly a part of many students' university experience, but because students are paid for work, its inclusion might bias results. In other words, students who know they must work to pay the bills might always choose the option with higher work hours, regardless of other factors. Rather than include work as a potential activity, we instructed students to view the allocation of time in the survey as allocation of time left over after essential activities have been completed. The role of the need or desire to work in students' decision- making requires careful consideration in future research.

Table 1. GPA, Activities, and Levels Used in the Choice Experiment

Achievement or Activity	Levels
GPA for the Semester	2.25
	2.75
	3.25
	3.75
Hours per week spent Studying	4 hours
	8 hours
Hours per week spent in Fraternity/Sorority/Club Activities	4 hours
	8 hours
Hours per week spent in Fitness/Sports/Recreation Activities	4 hours
	8 hours
Hours per week spent in Unstructured Social Activities	4 hours
	8 hours
Hours spent in Other Activities (Staying Home, Relaxing, Watching Movies, etc.)	4 hours
	8 hours

Note: In this choice experiment, students evaluated two scenarios, each with a level of GPA and a time commitment to each of five categories of activities. Figure 2 is an example of a choice question.

As with any choice experiment survey design, there is a trade-off between the number of survey questions and the number of activities and time levels. That is, the more activities, time levels, or both, the more questions that must be included to achieve adequate statistical performance. In the interest of providing a reasonable array of potential activities and variation among GPA levels, we opted to offer four possible GPAs and two possible time levels for each activity (four hours and eight hours).

Using the six categories and attribute levels in Table 1, there are 16,384 unique choice alternatives. To create a manageable survey, we follow the common procedure of identifying a question set (as a fractional factorial design) that optimizes the D-efficiency score (Lusk et al. 2003; Tonsor 2018). The final survey design had 17 choice sets and a D-efficiency score of 96. To avoid participant fatigue, we presented the students with smaller blocks drawn from the 17 sets (Schulz and Tonsor 2010; Tonsor, Schroeder, and

Lusk 2013; Tonsor 2018). We formed blocks of five by dividing 16 sets into blocks of four and then including the seventeenth set in each of those four blocks. The result was four blocks of five questions. These blocks were randomly assigned to students. The five choice sets given to students contained two alternative scenarios with varying levels of GPA and time assigned to activities. GPA was always listed first, and the order of activities was varied randomly across questions. Figure 2 shows an example choice experiment question. It is likely that some alternatives may be dominant. For example, if one option has less study time *and* a higher GPA than another alternative, that option would be more attractive to many or most students. We also face the possibility that the neither-A-nor-B option would dominate other alternatives, particularly for students who consider lower GPAs unacceptable. Such issues are common in choice experiment design. We followed Lusk et al. (2003) and left all dominant alternatives in the experiment as well as allowed the equivalent of the neither-A-nor-B option in the interest of improving the statistical properties of the experimental design.

	Option A	**Option B**	**Option C**
GPA for the Semester	3.25	2.25	Neither A nor B is preferred
Hours spent Studying	8	4	
Hours spent in Fraternity/Sorority/Club Activities	8	8	
Hours spent in Fitness/Sports/Recreation Activities	8	4	
Hours spent in Unstructured Social Activities	4	8	
Hours spent in Other Activities (Staying Home, Relaxing, Watching Movies, etc.)	4	4	
I would choose…	◯	◯	◯

Figure 2. Sample Choice Experiment Question

3 Conceptual Model

The idea of household production whereby the decision maker is both producer and consumer is well established (Becker 1965). The concept has been adapted to the university student's situation, in which the student's endowments and effort are inputs into the university experience and the student also consumes (or benefits from) education and attained human capital (Kelley 1975; Devadoss and Foltz 1996; Ballard 2014). Utility-maximizing students will allocate scarce resources among activities to optimize their university experience.

Empirically, utility is viewed from a random utility framework, whereby the random utility function is represented by a deterministic and stochastic component (Adamowicz et al. 1998; Lusk et al. 2003):

$$U_{ij} = V_{ij} + \varepsilon_{ij}\,. \tag{1}$$

In this formulation, U_{ij} is the utility the ith student receives from choosing option j, and ε_{ij} is the stochastic element.[2] V_{ij} is the systemic portion of the student's utility function determined by semester GPA and allocation of weekly time. The ith student faces the choice set C_i={A,B,C}, where A and B are random combinations of GPA level and time spent in each activity and C is opting to choose neither A nor B. The probability of choosing alternative j is:

$$\text{Prob}\left\{V_{ij} + \varepsilon_{ij} \geq V_{ik} + \varepsilon_{ik}; \forall k \in C_i\right\}. \tag{2}$$

[2] Time subscripts, reflecting multiple choices being made by each respondent, are omitted for presentation convenience.

Following Lusk, Roosen, and Fox (2003), assuming independently and identically extreme value Type 1 distributed errors in (1), this probability is equal to (Ben-Akiva and Lerman 1985):

$$\text{Prob}\{\, j \text{ is chosen}\} = \frac{e^{\mu V_{ij}}}{\sum_{k\in C} e^{\mu V_{ik}}}, \tag{3}$$

where μ is a scale parameter inversely related to the variance of the error term. Assuming that the utility function is linear in the parameters, it is expressed as:

$$V_{ij} = \delta\, GPA_{ij} + \beta_1 x_{ij1} + \beta_2 x_{ij2} + \beta_3 x_{ij3} + \beta_4 x_{ij4} + \beta_5 x_{ij5}, \tag{4}$$

where GPA_{ij} is the level of semester GPA, and x_{ijn} is the number of hours allocated to the n^th activity in a week for n = 1, 2, 3, 4, or 5. The five activities corresponding to x_{ij1} to x_{ij5} are listed in Table 1. Equations 3 and 4 form a conditional logit model. The scale parameter is assumed to equal one.

In this choice experiment, GPA differs from the typical product attribute in experiments focused on new or hypothetical products. That is, it is not a label or product characteristic. In fact, students completing the survey have an existing frame of reference regarding GPA and how they might influence its level. Tonsor (2018) used the comparable situation of including varying levels of average daily gain of livestock in a choice experiment targeted at purchase of inputs.[3] He points out that the producer frame of reference for average daily gain sets the stage for the use of transformed probabilities (Tversky and Kahneman 1992) in the decision. We posit the same in the study. Student GPA is directly relevant to the surveyed students, unlike hypothetical products or situations removed from their current situation and not directly related to their well-being. Consequently, we use each student's current GPA to modify equation 4 so that GPA gains and GPA losses are considered separately to identify asymmetries in responses to potential GPA increases and decreases.

$$V_{ij} = \delta_1 GPAGain_{ij} + \delta_2 GPALoss_{ij} + \beta_1 x_{ij1} + \beta_2 x_{ij2} + \beta_3 x_{ij3} + \beta_4 x_{ij4} + \beta_5 x_{ij5}. \tag{5}$$

Here, $GPAGain_{ij}$ is the absolute value of the difference between GPA level offered in the choice experiment alternative and the self-reported, current GPA of the i^th student when the offered GPA level is greater than the current GPA and zero otherwise. That is, it is the absolute gain in GPA, relative to actual GPA, that a student would realize from choosing an alternative. $GPALoss_{ij}$ is similarly defined to reflect absolute decline in the GPA being offered. All other definitions from equation 4 remain the same. The appropriateness of a prospect theory approach can be tested using the estimates of δ_1 and δ_2. Whereas expected utility theory suggests the responses to gains and losses are symmetrical, prospect theory allows asymmetry. We hypothesize that the impact of *GPAGain* will be positive and that of *GPALoss* will be negative. However, it is the relative impact of *GPAGain* and *GPALoss* that is central to prospect theory. If the absolute values of δ_1 and δ_2 are not equal, prospect theory is appropriate to explain student behavior.

[3] Average daily gain (ADG) is the average weight gain per day of livestock. Because livestock are sold on the basis of weight, this measure directly impacts profitability. Furthermore, livestock producers may influence ADG through management practices. This situation is analogous to student GPA, which is valuable to the student and can, to some degree, be influenced by students.

4 Results

The choice experiment survey described above was administered in fall 2018 at Kansas State University to students enrolled in two intermediate microeconomic theory courses.[4] The two courses are required for agricultural economics and agribusiness majors and minors and, therefore, the survey participants were primarily majors or minors in these areas. The courses were chosen for several reasons. First, their enrollees were mostly juniors and seniors. Only a few were sophomores, and none were freshmen. Hence, all the enrollees had a cumulative GPA reflecting at least a few semesters of coursework. Moreover, because the enrollees were not all at the same point in their university careers, the survey could capture variation in behavior and incentives reflecting nearness of graduation. No student was enrolled in both courses. To elicit participation, the survey was announced in advance, and students in both classes were allowed to use completion of the survey as a homework assignment. There were a total of 105 usable, complete responses. Descriptive statistics of the student characteristics are reported in Table 2.

Table 2. Summary Statistics of Student Characteristics

Variable	Definition	Mean	Std. Dev.	Min	Max
GPA	Self-reported, cumulative, current Kansas State University grade point average (4-point scale)	3.318	0.484	2.3	4
Female	= 1 if student is female, 0 otherwise	0.410	-	0	1
Senior	= 1 if student is a senior, 0 otherwise	0.419	-	0	1
Greek	= 1 if student is in a fraternity or sorority, 0 otherwise	0.353	-	0	1
Working	= 1 if student is working full or part time, 0 otherwise	0.723	-	0	1

Note: *N*=105.

Survey responses were used to estimate a conditional logit model (based on equations 3 and 4); attributed being effects were coded.[5] Results are shown in Table 3. Estimates in the first column are for all students, using the base model. Opt Out is a binary variable equal to one when the available alternative is Neither A nor B and is added to equations 4 and 5 for the estimation. The Opt Out variable indicates that a given observation is option C (Opt Out). In the conditional logit model, each question for a given student results in three observations: one for choice A, one for choice B, and one for choice C (neither A nor B). The estimated coefficient on this binary variable can be used to estimate the probability of the opt out option being chosen, all else equal. This approach is typical in analysis of choice experiments (Schulz and Tonsor 2010; Tonsor 2018). A choice must be made about the value of the activities offered in the Neither A nor B option. In many cases, simply setting the value at zero is conceptually appropriate. That is, opting out of the other available choices means that you do not experience a given attribute. However, assuming that a student would associate opting for neither A nor B with a GPA equal to 0 is not reasonable. Therefore, we set the value of GPA to the student's self-reported GPA in these cases. The assumption is that, by opting out, a student is basically indicating they are happy with their current situation. The negative coefficient indicates that, all else equal, students were less likely to choose the Opt Out option or, in other words,

[4] The Institutional Review Board of Kansas State University determined this project to be exempt from further review under 45 CFR §46.101, paragraph b, category: 2, subsection: ii. The complete survey is available on request from the authors.
[5] Our final models are variants of traditional conditional logit models. Alternative logit models, including latent class specifications, revealed no significant preference heterogeneity.

Table 3. Expected Utility Theory: Conditional Logit Estimates

Variable	All Students	Students with GPA < Median	Students with GPA > Median
Opt Out	-2.366***	-1.676***	-3.408***
	(0.192)	(0.240)	(0.355)
GPA Level	1.951***	1.701***	2.741***
	(0.155)	(0.215)	(0.291)
Weekly Hours Devoted to Greek Activities	0.134	0.168	0.149
	(0.088)	(0.123)	(0.140)
Weekly Hours Devoted to Study	-0.069	-0.345***	0.128
	(0.087)	(0.129)	(0.141)
Weekly Hours Devoted to Unstructured Social Activity	0.081 (0.103)	0.095 (0.144)	0.037 (0.172)
Weekly Hours Devoted to Sports/Rec/Fitness	0.121	0.089	0.165
	(0.086)	(0.110)	(0.161)
Weekly Hours Devoted to Other Activities (Staying Home, Relaxing, Watching Movies, etc.)	0.374*** (0.078)	0.576*** (0.117)	0.218* (0.126)
AIC	742.676	372.331	350.218
Percent of Correct In-sample Predictions	71.24%	71.3%	72.3%
N	1575	795	780

Notes: One hundred and five students completed the survey. Each student answered five questions and each question had three possible choices for 1575 (105 x 5 x 3) observations in the full sample MNL model. ***, **, and * note statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are listed in parentheses.

choose their current situation over other offered choices.[6] Student GPA is statistically significant and positively related to the probability that a student chooses a given alternative. This result is intuitive and indicates students are concerned about GPA when making time allocation choices. Interestingly, time devoted to Greek activities, Unstructured Social Activity, and Sports/Rec/Fitness does not statistically impact the probability of selecting an alternative. Even the coefficient on Hours Devoted to Study, which has a negative sign as hypothesized, is statistically insignificant. The only time category that is statistically related to student choice is Other Activities, which is unstructured recreational time. The more free time available, the greater the probability that a student will choose an alternative.

Existing research indicates that previous level of academic success is important in explaining student success or behavior. For example, previous GPA is found to be positively correlated with student attendance and course grade (Devadoss and Foltz 1996). A related finding is that the impact of introducing prepared lecture notes differed depending on a student's ACT or SAT score (Kelley 1975). To investigate the presence of such differences among student preferences in our survey, we divided the sample at the median self-reported GPA. The conditional logit model was re-estimated separately for (1) students with GPAs below the sample median and (2) students with GPAs above the sample median. The results are reported in the second and third columns of Table 3, respectively. There is a statistical difference between the choices of relatively higher-achieving and lower-achieving students. Higher-achieving students value GPA more. Specifically, GPA and the probability of choosing an alternative are positively related for both groups, but the impact is greater for the higher-achieving students. Hours Devoted to Study does not statistically impact the higher-achieving student choices, but it has a large, statistically significant negative

[6] We estimated two formulations: one in which the opt out GPA = 0 and one in which opt out GPA = self-reported GPA. Only the magnitude of the coefficient on Opt Out varied. The statistical significance of impacts across time categories was identical, and magnitudes of those coefficients did not change substantially.

impact for lower-achieving students. Finally, lower-achieving students valued free time (Other Activities) at much higher levels than higher-achieving students. Both groups treat it as a good, but the impact on likelihood of choosing an alternative is greater for the lower-achieving students. These results imply that the two groups of students may be motivated differently. Higher-achieving students are not put off by additional study time, and they value marginal improvements in GPA. Lower-achieving students view study time as a "bad." There are several possible explanations for this outcome. Higher-achieving students may be more efficient or effective at studying (Kelley 1975; Schmidt 1983) and, therefore, not as averse to it. Also, students with higher GPAs may enjoy learning or consider the additional effort worthwhile.

Next, we specified a conditional logit model using equations 3 and 5. The purpose of this specification was to evaluate students' time-allocation decision using prospect theory, instead of expected utility theory. Specifically, this specification allows for asymmetry between responses to GPA gains and losses. The estimation results of the prospect theory model are reported in Table 4.[7] The statistical significance of Hours Devoted to Other Activities remains in this formulation. The magnitude of coefficients on hours devoted to each activity change very little compared to the base expected utility model (Table 3). However, the difference in the impact of GPA losses versus gains is striking. The signs are as expected. A GPA decrease (increase) lowers (raises) the probability of choosing a given alternative. However, the decrease in likelihood from a one-point GPA loss is 4.6 times as great as the increase from a one-point gain. The relative reactions are statistically different. We conducted a Wald test where H_0: $|\delta_1| = |\delta_2|$. The Chi-squared test statistic was 25.14, which means we rejected the null at a significance level of < 0.001. The

Table 4. Prospect Theory: GPA Gains and Losses Conditional Logit Estimates

Variable	Coefficient Estimate (Standard Error)
Opt Out	-2.926***
	(0.236)
GPA Gain (|GPA Offered – Reported GPA where GPA Offered > Reported GPA)	0.569**
	(0.288)
GPA Loss (|GPA Offered – Reported GPA where GPA Offered < Reported GPA)	-2.664***
	(0.228)
Weekly Hours Devoted to Greek Activities	0.157*
	(0.087)
Weekly Hours Devoted to Study	-0.082
	(0.085)
Weekly Hours Devoted to Unstructured Social Activity	0.039
	(0.101)
Weekly Hours Devoted to Sports/Rec/Fitness	0.101
	(0.085)
Weekly Hours Devoted to Other Activities (Staying Home, Relaxing, Watching Movies, etc.)	0.330***
	(0.078)
AIC	720.926
Percent of Correct In-sample Predictions	70.67%
N	1575

Notes: One hundred and five students completed the survey. Each student answered five questions and each question had three possible choices for 1575 (105 x 5 x 3) observations in the full sample MNL model. ***, **, and * note statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are listed in parentheses.

[7] In this case, the value of GPA for both *GPAGain* and *GPALoss* was set to zero in the Opt Out scenario. This value is conceptually appropriate, assuming that the student uses current GPA as a reference. Opting out in this case would be to keep current GPA and experience no gain or loss.

statistical difference in the relative responses to gains and losses in GPA suggests prospect theory is more appropriate than expected utility theory in explaining student choices related to GPA and time trade-offs.

It is possible to derive willingness-to-pay (WTP) estimates from the conditional logit coefficient estimates. In typical choice studies, in which participants are presented with varying prices, WTP is calculated in units of currency (Lusk et al. 2003; Lusk and Hudson 2004; Tonsor, Schroeder, and Lusk 2013; Tonsor 2018). However, our relevant comparison is between GPA points and hours allocated to various activities. For example, we can estimate how many GPA points are required to induce a student to study another four hours. In this case, the concept is to calculate utility (equation 4 or 5) at four hours of study and at eight hours of study with GPA and all other variables at the same level. Then, in the case of the utility level associated with eight hours of study, GPA is increased until the two utilities are equal. The difference between GPA in the two cases is the willingness to trade GPA points for hours of study. Mathematically, this willingness to trade is equivalent to taking the ratio of the coefficient on Hours Devoted to Study to the coefficient on GPA and multiplying by two (Lusk, Roosen, and Fox 2003).[8] Table 5 contains WTP estimates and delta method 95% confidence intervals across all models. The interpretation of the WTP measures is points of semester GPA a student would trade for four more hours per week of a given activity, ceteris paribus.[9] Hours spent studying is statistically significant only in the expected utility model for lower-achieving students. Responses from these students indicate that they would forgo 0.406 semester GPA points to avoid four hours of weekly study.

Table 5. Willingness to Pay in Semester GPA Points per Weekly Time of Selected Activities with 95% Confidence Intervals

	Weekly Hours				
Points of:	**Greek**	**Study**	**Social**	**Rec/Sports /Fitness**	**Other Activities**
GPA (all students)	0.137**	-0.071	0.083	0.124	0.383**
	[0.268, 0.006]	[0.060, -0.202]	[0.213, -0.047]	[0.256, -0.008]	[0.516, 0.250]
GPA (students with GPA < Median)	0.197	-0.406**	0.112	0.105	0.678**
	[0.407, -0.013]	[-0.195, -0.617]	[0.317, -0.093]	[0.314, -0.104]	[0.891, 0.464]
GPA (students with GPA > Median)	0.109	0.093	0.027	0.121	0.159
	[0.283, -0.065]	[0.269, -0.082]	[0.201, -0.147]	[0.297, -0.056]	[0.336, -0.017]
GPA Gain (all students)	0.552	-0.289	0.137	0.355	1.160**
	[1.405, -0.300]	[0.547, -1.125]	[0.966, -0.692]	[1.192, -0.481]	[2.009, 0.311]
GPA Loss (all students)	-0.118	0.062	-0.029	-0.076	-0.248**
	[-0.258, 0.022]	[-0.079, 0.202]	[-0.170, 0.111]	[-0.216, 0.065]	[-0.390, -0.105]

Notes: WTP = (MNL coefficient for each activity/MNL coefficient for GPA) x 2. Confidence intervals were calculated using the delta method. Presented levels of activity hours were either four or eight. These effects are coded: 4 is the reference category (= -1). ** indicates statistical significance of at least 0.05. The WTP estimates in the first three rows are based on the three models in Table 2; the last two rows are based on those in Table 3. The category Other Activities is unstructured free time, as shown in Figure 2.

We can also consider the implied corollary that, in order to be motivated to add four hours of study per week, a low-achieving student would have to expect a greater-than-0.406 increase in semester GPA. Such a WTP measure seems quite abstract, so it is helpful to give some context. Assume a student is enrolled in five courses, each of which counts for three credit hours. In this case, a 0.4 decrease in semester GPA corresponds to a one-letter grade decrease in two of the courses. This is a non-trivial change in GPA and is

[8] It is necessary to multiply by two because hours devoted to activities were effects coded. In model estimation, the reference category of four hours was set equal to -1, and eight hours was set equal to one.

[9] To put the four hours per week measure in context, adding 45 to 50 minutes per weekday would be one way to achieve this change. Adding 45 to 50 minutes per weekday would be a reasonable way to add study time. For example, a student might meet with a tutor or study group for a daily session each weekday.

consistent with Kelley (1975), who observed that, depending on the way GPA is calculated, only teaching innovations with major impacts on student achievement will be demanded by students. We see a similar finding here in that lower-achieving students require a substantial boost in GPA to offset the loss in utility derived from study time. The more common preference structure, as illustrated in Figure 1, could be that academic achievement matters, but mainly to the extent that it allows or disallows the binary achievement of a university degree. This structure holds true especially for students with a current GPA in the lower half of the sample.

WTP results also demonstrate that the statistical impact of hours devoted to Other Activities (i.e., free time) is generally significant. This result persists with different model specifications. The idea of completely free time with no express or implied commitments could be very attractive to university students. Results of the base model for all students indicate that students are willing to give up 0.383 semester GPA points for another 4 hours of free time each week. When the sample is split at the median GPA, the impact is not statistically significant for the higher-achieving students. But lower-achieving students would trade 0.678 semester GPA points for an additional 4 hours of free time per week. Note that these students assign a greater value, in absolute terms, to free time than to study time.

The final two rows of Table 5 report WTP estimated from the prospect theory model (Table 4). In terms of Other Activities, there is a stark difference between WTP for GPA Gain and WTP to avoid GPA Loss. Students will give up 4 hours of free time per week to avoid losing 0.248 semester GPA points. On the other hand, they must be rewarded with a gain of 1.160 GPA points to sacrifice this amount of free time. There are likely several reasons for this implied loss aversion ratio of 4.6. First, if university is indeed a screening output (Kelley 1975), as discussed earlier, a GPA loss puts a student at risk of dropping below minimum GPA requirements for academic probation or expulsion, both of which would prohibit graduation. Conversely, if a student is currently above such a minimum, a GPA gain contributes nothing to the binary achievement of graduation. This consideration would seem to especially apply to lower-achieving students with a GPA close to academic probation or expulsion. Second, higher-achieving students might also reasonably be loss averse. These students are likely receiving scholarships, fellowships, or other benefits with minimum GPA requirements. For them, a minor addition to GPA would offer little benefit, but a decrease that brought GPA below the threshold for a scholarship would be detrimental.[10]

Another notable finding is the relatively large loss aversion ratio. Many studies involving money and short-term choices find a loss aversion ratio of around 2 (Abdellaoui, Bleichrodt, and Paraschiv 2007). We find the noticeably higher ratio of 4.6. This higher ratio could be due to the stakes involved in the current scenario. In many choice experiment applications, participants face choices regarding a one-time purchase or monetary decision. In the case of this research, determining the GPA is basically a non-repeatable event that could impact quality of life and earnings for years to come. In this context, it is reasonable that GPA loss aversion would be high relative to monetary loss aversion in other choice experiment contexts.

5 Implications and Further Research

This study implemented a choice experiment survey targeted at 105 students enrolled in intermediate microeconomic theory courses in the Department of Agricultural Economics. Students were presented with alternatives that combined hypothetical GPA levels with time allocated to broad categories of activities. The experiment results were analyzed with conditional logit models. This approach is consistent with expected utility theory. Results show that lower-achieving students dislike allocating time to studying and that study time has no impact on the choices of higher-achieving students. All students seem to value Hours Spent on Other Activities (or free time) more than other ways of allocating time. Revising the model to separate GPA gains and losses allows a novel look at student time allocation from a prospect theory approach. Indeed, students are loss averse in terms of GPA points. They dislike losing GPA points about 4.6 times as much as they enjoy gaining GPA points.

[10] For students with a 4.0 GPA, a decrease could have a negative psychological impact and put awards out of reach.

The limitations of the findings should be carefully considered. The students were all enrolled in agricultural economics courses at Kansas State University, which is a major land grant university. Most, but not all of the students, were agricultural economics or agribusiness majors. Some of the particular findings may be specific to land grant schools, Kansas State University, or agricultural economics/agribusiness majors. Within our sample, we found no heterogeneity among groups as defined by class, gender, and so on. However, it may exist and be identifiable in a broader sample in future research. One specific area would be to consider the impact of working full time or part time on students' time trade-offs. Another concern is that student decisions have been found to be biased by current conditions (Simonsohn 2010). However, bearing the limitations in mind, there is evidence that the results are credible. First, the general findings confirm what other studies on the productivity of student time have suggested. Second, the trade-offs chosen by students are realistic (see footnote 4). Finally, student choice experiment responses are consistent with student university goal rankings. This internal consistency offers confidence that students were taking time to consider their choices and understood what was being asked. This confidence in the basic experimental design and research question offer a base on which to build future research that expands the study across multiple majors and institutions. We recommend conducting the experiment over different semesters as way to control for students being biased by their immediate situation (Simonsohn 2010).

Though caution is warranted in generalizing the findings, they are rich with implications for instructors, academic advisors, and other stakeholders concerned with university student experience. Choice experiment results, taken with the ranking of university goals, confirm that students likely see a university diploma as the most valuable product of the university experience. Marginal improvements in GPA are not highly valued, but losses in GPA are more severe in absolute terms, particularly for lower-achieving students. With this finding in mind, instructors should prioritize giving students big-picture course guidance and making clear what is generally required to achieve certain letter grades. This information helps students understand what is needed to actualize major grade changes and avoid GPA losses. By contrast, fine-tuned advice will likely appeal to higher-achieving students. Results highlight the difference between the decisions of higher- and lower-achieving students and the nuances of effectively teaching both groups. As instructors we must realize, painful as it might be, that many students will not value minor grade improvements or a marginal increase in knowledge. Their motivations and incentive structures often differ from our own. However, minor grade or GPA improvements will likely be valued by higher-achieving students (Table 3), possibly because these students are often in a position to benefit from a marginal GPA increase. For example, a student targeting graduate school might benefit from increasing GPA from 3.3 to 3.7. Our results imply that tailoring advice and direction on the basis of student goals and achievement will have a positive impact on their utility and university experience.

Academic advisors can similarly benefit from the study findings, specifically from realizing that many students value the diploma over all other aspects of the university experience. Accepting that this perspective is not necessarily a sign of laziness is helpful in developing empathy and rapport with students. It can reduce frustration when advice directed toward improving academic achievements seems to fall on deaf ears. Additionally, given the high value placed on free time, the study findings suggest that helping students to understand good time management practices and the possible future value of current activities will improve the student experience.

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Teaching and Educational Methods

Enhancing Student Engagement in a Changing Academic Environment-Tested Innovations for Traditional Classes and Online Teaching

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Abstract
Agriculture is a global industry that constantly innovates and increasingly uses cutting-edge technology. A great number of job opportunities exist because this important sector of the economy is looking to recruit motivated and ambitious young people. Meanwhile, the academic environment is changing. Many programs experience increased class sizes and are introducing online curricula. Addressing these simultaneous challenges, eight teaching scholars from agricultural and applied economics programs presented their teaching approaches in a track session at the 2019 AAEA Annual Meeting. This article continues the conversation about specific teaching innovations tested in traditional classroom settings and online environments in an attempt to share lessons learned with a broader audience. Many of the insights presented here are easily adaptable when teaching remotely and will remain relevant once campuses reopen.

1 Introduction

Demand for well-trained college graduates with a major from agricultural degree programs have increased over the last five years. An estimated 57,900 high-skilled annual job openings in agriculture, renewable natural resources, and environment fields were added to the U.S. economy between 2015 and 2020 (Purdue University 2015). The growing local and regional food movement created additional job opportunities, and the USDA already invested over $1 billion to attract new producers to farming and food-related businesses (Vilsack 2016). Although the current unprecedented economic downturn will affect all sectors of the economy, these agricultural-related careers might be relatively less impacted.

Universities and colleges tasked with supplying these graduates have already been adapting to new technologies and methods to improve the quality of teaching. In particular, the use of online resources has continuously increased over the last decade. About one third of students enrolled in higher education took at least one course online (Allen and Seaman 2013; Kentnor 2015), and the rapid switch to remote instructions as a response to the COVID-19 pandemic will likely accelerate changes in the teaching and learning environment. Nevertheless, important questions remain: how can universities further a renewed interest in agriculture and resource management and prepare students for the pressing challenges of our time? More specifically, how can we increase student engagement within changing academic structures toward larger class sizes and remote access? How can we create meaningful connections and applications, awaken curiosity, and develop a desire to go beyond graded requirements?

This article discusses innovative teaching approaches tested in traditional classroom settings and online classes to begin answering these and related questions.[1] We first provide a short overview of the existing literature on student engagement and describe our successful approaches to increase student engagement implemented in traditional classrooms. We then summarize existing literature on teaching in an online environment and present our approaches that modified or re-envisioned the use of online learning tools and social media for large classes. Finally, we conclude by reflecting on the challenges ahead.

2 Innovations in Traditional Classroom Settings

The existing literature clearly documents a positive correlation between student engagement and academic achievement (Carini, Kuh, and Klein 2006; Trowler and Trowler 2010; Lei, Cui, and Zhou 2018). Student engagement can be defined as a multifaceted, dynamic process with behavioral, cognitive, and emotional dimensions (Fredricks, Blumenfeld, and Paris 2004; Wang and Holcombe 2010). More specifically, Fredricks et al. (2004) discuss that engagement requires students' positive conduct, such as following the rules and adhering to classroom norms, as well as participating and involving in academic tasks (i.e., behavioral dimension). They also stress the importance of students' investment in learning and self-regulated strategic studying (i.e., cognitive dimension) as well as students' affective reactions to and connectedness with other students and teachers (i.e., emotional dimension). In other words, student engagement observed as active class participation needs to be fueled by the desire to go beyond class requirements and challenge seeking, as well as a deeper emotional connection with the material, their peers, and instructors (Trowler 2010; Quaye and Harper 2015).

Although student preferences, classroom context, and institutional factors can all contribute to a higher level of student engagement (Fredricks et al. 2004), teacher actions remain central in student-centered pedagogies (Kuh et al. 2006). The term "pedagogies of engagement" was first introduced by Edgerton (2001), although pedagogical developments of the 1990s already emphasized collaborative or cooperative learning, inquiry and problem-based learning, team projects, and authentic learning as a basis for student-centered pedagogies (Barrows and Tamblyn 1980; Johnson, Johnson, and Smith 1991; Jonassen and Rohrer-Murphy 1999). In a survey of 1,246 college students, Zepke, Leach, and Butler (2014) found that the three most important teacher actions to increase student engagement are: providing feedback to improve student learning, teaching in ways that enable students to learn, and being enthusiastic about the subject. Carefully designed tasks can further enhance engagement in learning if they are perceived as authentic, provide students with opportunities to assume ownership of their actions, and allow collaboration (Newmann 1991; Newmann and Wehlage 1993). Helme and Clarke (2001) further find that cognitive engagement is more likely to occur when students are asked to work with peers on novel tasks that have personal meaning. Similarly, Herrington and Oliver (2000) and Herrington and Herrington (2006) emphasize a framework that situates learning activities within real-world circumstances and provides immersive learning tasks in realistic learning contexts. Finally, Burns and Chopra (2017) point out that student learning can be enhanced through industry involvement.

Below we discuss five approaches that translate these findings into teaching innovations implemented in large undergraduate classes. Barkley, Kiesel, and Lacy used in-class assignments, peer-based learning activities, and teaching with experiments to increase student engagement in large classes and improve learning outcomes. Zuo and her colleagues reflect on three implemented approaches to authentic learning aimed at engaging students in global agriculture. Finally, Hanson's description of the Farm Credit Fellows program serves as an example of a successful industry collaboration.

[1] These innovations and shared lessons learned were presented in the track session "Increasing Student Engagement and Attracting Talent in a Changing Academic Environment" sponsored by the Teaching, Learning, and Communications and Agribusiness Economics and Management sections at the 2019 AAEA Annual Meeting. The feedback we received motived us to share our experiences more broadly within our discipline.

2.1 Using Small Group In-Class Assignments Instead of Quizzes

Andrew Barkley teaches a required course in applied microeconomics at Kansas State University. The course is the second semester of a two-semester, Junior-level sequence in intermediate microeconomics applied to food and agriculture, with calculus as a prerequisite. Barkley describes his in-class exercises assigned during this course as *Skill Builders*.

He incorporates these assignments into every lecture. The short assignments cover material from the previous lecture, and take about 5 minutes. Barkley's initial idea was to encourage students to attend every class, as well as to review their notes from the previous lecture. He did so by giving a quiz at the start of each lecture.

Although this worked well for some students, particularly serious students who systematically reviewed the material, other students experienced high levels of performance and/or test anxiety. The classroom environment suffered for students who did not perform well on the quizzes, and he frequently had to deal with incidents of cheating. Barkley decided to replace the quizzes with daily in-class assignments, covering the most rigorous and challenging material from previous lectures.

These assignments gave students the opportunity to apply challenging economic concepts to food and agriculture and to see questions similar to those on upcoming exams. The assignments are completed and submitted by each individual, transforming work and discussions with other classmates from cheating to an encouraged activity. Not only did this new approach result in higher-order learning and better learning outcomes, it also contributed to a positive and less threatening learning environment.

The assignments are typically applications of microeconomics to issues in food and agriculture, including profit-maximization, advertising, the causes and consequences of monopoly and monopsony in food and agricultural markets, and game theory. Students were able to ask for help when working on these assignments, and the grading provides a useful mechanism for reinforcement, encouragement, and feedback. Finally, grading these *Skill Builders* helped Barkley to revise the course material and better align it with student interests and possible career choices.

In summary, although designing and implementing these types of assignments was costly in terms of reduced coverage of course material and additional time spent on preparation, implementation, and grading, the benefits seemed to have outweighed these costs. Benefits include increased class attendance, higher levels of student participation in lectures, enhanced learning outcomes, a more positive class environment, and improved student-teacher relationships. Feedback from students is positive. Quizzes were popular with good students who were motivated to review their notes before each lecture, but were unpopular with struggling and anxious students. *Skill Builders* appear to be a successful way to provide extra practice with difficult concepts and reward class attendance.

2.2 A Peer-Based Learning Approach Supported by Group Projects, Clicker Participation Questions, and Instructional Videos

Kristin Kiesel redesigned the Intermediate Microeconomics course taught in the Agricultural and Resource Economics Department at the University of California, Davis, over several quarters in an effort to incentivize peer-based learning. She started with the introduction of a quarter-long group project that asks students to play a game based on oil production by the Organization of Petroleum Exporting Countries (OPEC). Students are divided into groups representing OPEC countries. They are given initial oil reserves, historic prices, production cost, and the rules of the game.[2] Students then play several rounds of this game and submit production quantities for their assigned countries as low-stakes assignments throughout the quarter. First, they are asked to develop strategies in a scenario that resembles perfect competition. The game then moves to a scenario that represents an oligopoly market structure. Finally, students are

[2] Several descriptions of an OPEC game as a teaching tool are available online. Kiesel's implementation of the game built on instructions posted by Borenstein and Bushnell (see http://faculty.haas.berkeley.edu/borenste/mba212/OPECgame.pdf) and her exposure to a version of this game used by Sofia Villas-Boas during a visiting assistant professor appointment at the University of California, Berkeley, in 2015.

encouraged to form a cartel, and one section is dedicated to allow students to discuss possible cartel agreements.[3] These submissions parallel the coverage of market structures and firm behavior in lecture and allow students to continuously apply the taught material. Kiesel shares the resulting market price and overall supply after each submission during lectures and encourages students to ask for feedback from the TAs or herself. One key aspect of this game is that students are submitting quantities repeatedly under each scenario. It allows students to reflect on their choices under consideration of the shared market outcomes and additional feedback. Prior to a detailed discussion of the game during her last lecture that also serves as a final exam review, students are asked to submit a memo or project report. It allows them to review the material covered throughout the quarter, reflect on their submissions, and describe what they would do differently. This opportunity to review their strategies and describe what they have learned serves as a high-stakes assignment.

Although many students were appreciative of this real-world application, others struggled and did not actively contribute to group discussions. Kiesel continued to refine instructions and created additional resources to support the game. To further support student engagement, Kiesel also incorporated clicker questions into her lectures during the following quarters. These questions appear throughout each lecture and are graded based on participation and correctness.[4] In contrast to taking short weekly quizzes at the beginning of lecture that test whether students complete the assigned readings, students can talk and consult their peers while each question remains open. In a final revision and attempt to strengthen her peer-based learning approach, Kiesel also created and posted learning glass videos that feature students explaining economic concepts.[5] These short videos (10–15 minutes) allow students to review key concepts covered in lecture. Featuring their peers is further intended to motivate students to try to learn from each other and explain the covered material in their own words.

Lecture attendance increased immediately after the implementation of clicker questions. More importantly, however, the group project, the opportunity to discuss responses to clicker questions, and the learning glass videos that featured students reinforced each other. They allowed students to increase their engagement with the material and interaction with their peers. More students started actively participating in lectures and took ownership of the OPEC game, improving learning outcomes significantly. While the introduction of the OPEC game alone allowed 32 percent of the students to improve their individual performance, 73 percent of students were able to improve their performance (measured by a received higher grade for the final as compared to the midterm) once all components were implemented. Furthermore, these innovations significantly improved students' perceptions of their learning as expressed in increased numerical scores and enthusiastic comments on their student evaluations. One student remarked: "Even though I may not earn an A in the course, I was able to engage with the material in a way that most students never get the chance to."

2.3 Teaching with Experiments in Large Classes

Many classroom activities can seem inapplicable to large class sizes. It is more challenging to keep students engaged as class sizes grow. However, with the right amount of preparation, classroom games can be a useful "learning-by-doing" strategy even for large classes. Games do not have to be self-created; there are many games for principles courses published on a website "Games Economics Play," maintained by Delemeester and Brauer (2010). Katherine Lacy adapted a number of these games to introduce material in her principles of microeconomics courses taught in the Economics Department at the University of Nevada, Reno.

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[3] Except for the first scenario that combines all groups into one game, four parallel games are played with each section representing one independent game.

[4] One question is randomly chosen from each lecture to assign participation points for that lecture. One point is given if a response was received, and an additional point is added if the question was answered correctly.

[5] Learning Glass technology uses specialized glass and lighting to create a transparent white board that illuminates writing with neon markers while the instructor is able to look directly into the camera. See https://video.ucdavis.edu/media/Competitive+Markets/0_nbjgavbl for an example of a video featuring Kiesel.

Lacy often uses games before introducing the material. This allows students to experience the material firsthand and provides the class with examples to reflect back on when discussing the material. For example, diminishing marginal product can be a challenging concept for introductory economics students. To provide students with firsthand experience of diminishing marginal product, a widget production game is introduced before the production chapter. Students are placed in groups of 7–8 students asked to produce as many "widgets" as possible in a given amount of time starting with 1 worker.[6] The next round introduces a second worker, third round introduces a third worker, etc. When it comes time to introduce diminishing marginal product of labor, Lacy allows students to comment on why they believe production did not increase as fast when adding workers when there were already 5, 6, or 7 students working compared with adding workers when only 1, 2, or 3 students were working. Students often describe the idea of diminishing marginal product of labor, which allows Lacy to formally define the economic term while using the class production data.

In a typical Principles of Microeconomics course, Lacy begins the second class with a game to introduce the circular flow diagram. Because of time constraints in her course calendar, she does not introduce supply and demand using games, but many games exist on the "Games Economist Play" website (Delemeester and Brauer 2010). When introducing consumer behavior in game theory, Lacy has students play a series of prisoners dilemma games and a game called 21 Flags to introduce backward induction. The next two games introduce environmental economics. Specifically, a common pool resource game using a "pool" of extra credit points and a pollution permit game developed by Caviglia-Harris and Melstrom (2015). When it comes time to introduce firm production, Lacy uses the widget production game previously mentioned. Finally, a game developed by Brouhle (2011) is used to introduce the class to Oligopolies.

Reflecting on her lessons learned, she emphasizes that early preparation is the key to a successful learning activity executed during lecture. She found that she could save valuable classroom time by providing the game/experiment instructions to the students before class and asking them to read the instructions beforehand. To ensure students read and understand the instructions, she then started her lectures with a pre-game quiz related to the instructions. This allows her to have a guided instruction discussion to clear up any misunderstanding before the game begins and provides students who did not read the instructions beforehand with information about the game. She also strongly advises not to start the game before the instructions are completely explained. Once students have started talking, all focus on the instructor is lost and not easily recovered.

During the game, she utilizes student response systems (clickers) to collect data and answers.[7] Additionally, early preparation comes in handy when the game does not work out as planned. Having responses and prepared discussions for these situations can help create valuable learning experiences even when things do not go as expected. Finally, Lacy used prizes, such as extra credit points or candy bars to encourage thoughtful participation and motivate students to develop winning strategies for the games. Once the games are completed and before prizes are distributed, she also asked students to complete a game-ending survey during which students summarize what they have learned from the activity in a couple sentences. This provided students with time to reflect on the game outcomes and connected them to the course material. This feedback has also allowed Lacy to adjust the games/experiments and ensure that

[6] Lacy has used many different types of "widget" definitions. The first widget production attempt requested students fold a piece of paper eight times and write "ECON WIDGET" on the paper with a provided sharpie (the limiting factor was the sharpie). However, this method used a lot of paper. Other widget production attempts included folding a piece of paper four times and stapling the four corners, folding paper airplanes and writing "ECON JET" on the wing using provided sharpie, placing paperclips along the outside of file folders, and producing rice by writing "rice" as many times as possible on a 8.5 × 11 inch sheet of paper. The most successful attempt has been the airplane production.

[7] However, it is important to always have a backup plan on how the students can submit answers if the clicker system fails. For example, Lacy brings copy paper to class on game days so if the clicker system is not working as expected, students can put their answers on sheets of paper and display them at the same time. Or if a TA is available, the TA may assist in collecting answers papers and compiling data.

student learning matches her learning objectives for the activity. In game feedback and on teaching evaluations, students have commented on their enjoyment of the games and appreciate the ability to have a more hands-on learning opportunity for more challenging concepts.

2.4 Three Classroom Practices to Engage Students in Global Agriculture

Global agriculture is an important subject area in which we could usefully engage our students. Appreciation of the interconnection and a comprehensive understanding of global agriculture are imperative for students' future success in the agricultural sector. Global perspectives arise naturally within agricultural economics curricula as topics of international trade, global agribusiness, and international economic development are commonly discussed. However, without offering an authentic learning environment, it can be challenging for students to comprehend global agriculture in a real-world context. While study abroad courses/programs are popular in this context, financial barriers and time constraints might put participation out of reach for some students.

Teaching in the Department of Agricultural and Resource Economics, Na Zuo and her colleagues found ways to engage students in global agriculture while learning locally at the University of Arizona. Utilizing the Authentic Learning model (Herrington and Oliver 2000) as the pedagogical framework, they examined three practices to bring real-world authentic context to the classroom. The first classroom practice was conducted in the course *The Economics of Futures Markets,* and it was a ten-week trading simulation on the *StockTrak* platform.[8] Students were provided with $500,000 of imaginary money and executed a number of different transactions based on real-time prices. Students were also asked to identify any events that affected the price of a commodity on which they had an open position and to cite news articles detailing the event. The objective was to encourage students to connect how policy changes, trade barriers, or weather events can affect global commodity prices, building an understanding of the connectedness of global agriculture and international trade. The second intervention was launched in an agribusiness management course, where a case study on a multinational retail chain was used to guide students to practice collaborative decision making. The information and data in the case study of interest provided an authentic context that demonstrated various entry modes to global markets used in a real multinational corporation. The case study supported collaborative construction of knowledge: in a 50-minute case session, students first worked collaboratively in groups on the case questions; then all groups were invited to contribute to a class worksheet, which then guided class discussions. The third classroom practice incorporated real-world example-based instructions in a general education course on the global food economy. It created a teaching and learning environment that utilizes real-world examples, collaborate group discussions, and team projects. Based on student responses, Zuo, Josephson, and Scheitrum (2019) found that students reported an increased understanding of and interest in global agriculture after these interventions were introduced in three classrooms, respectively.[9]

2.5 The Farm Credit Fellows Program: Collaborations with Industry to Enhance Learning

The Farm Credit Fellows program at North Dakota State University is an example of increasing student engagement through unique class structure and industry collaboration. The program blends an agricultural lending class with off-campus training and learning opportunities provided by three local Farm Credit System associations. Erik Hanson asks students to examine three or four unique case studies each year as experiential learning exercises.

These case studies are based on realistic example loan applications created by the participating associations, and students make recommendations for loan approval based on historical income statements, balance sheets, and other application information. Several other case studies are included in the Fellows program's off-campus events. For example, students showcase their skills at a loan discussion

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[8] Available at https://www.stocktrak.com/.

[9] All three interventions are further detailed by Zuo et al. (2019).

forum where they analyze case studies alongside loan officers and credit analysts. A case study is also used as the course's final project. Altogether, the Fellows program allows students to repeatedly apply key definitions and calculations learned in class. When tested after the course, Fellows program participants earned significantly higher scores on a financial assessment than students in the university's other agricultural finance courses. Perhaps more importantly, students have multiple opportunities to sharpen their analytical skills and technical communication abilities, and they are particularly excited when they are able to discuss the lending cases with industry professionals. These interactions allow students to gain confidence and build their professional networks prior to entering the workforce. Indeed, Fellows program alumni have strong placements at local Farm Credit System associations and banks.

3 Innovations in Online Classes and the Utilization of Online Tools

In addition to increases in class sizes, higher enrollment numbers have resulted in more online course offerings and an emphasis of online tools in higher education. In 2013, 26 percent of students at U.S. colleges and universities took at least one course online (McPherson and Bacow 2015), and four years later, this number had risen to just over 33 percent (National Center for Educational Conditions 2019). Despite their prevalence in the news, distance education courses offered by distance-only institutions enrolled only 2 percent of all undergraduate students in the United States in 2017 (National Center for Educational Conditions 2019). Students are much more likely to take online courses from institutions with a physical presence. Many land grant universities have been considering online courses as part of their curriculum because they can provide greater access and more flexibility to students. The recent COVID-19 pandemic has precipitated a further interest in considering these options, and many faculty have gotten a crash course in online teaching. Deming et al. (2015) address the effect of online courses on the extensive margin of education and ask whether online learning can affect the education cost curve. Controlling for selectivity (a proxy for educational quality), they find that institutions with more online classes have lower tuition prices. Also, in a recently published paper, Goodman, Melkers, and Pallais (2019) use data from a highly ranked MS degree program in Computer Science at Georgia Tech to provide the first evidence that student access to education via online course offerings can increase overall enrollment.

The use of online tools can take a number of forms. Even when classes are taught in traditional face-to-face classrooms, instructors increasingly use online tools and information technology. Instructors may post slides or recordings of lectures online, enable students to submit homework or receive feedback online, engage students using online economic experiments or games, assess learning outcomes using online quizzes and exams, and encourage peer-to-peer interactions on social media or online discussion boards (Allgood, Walstad, and Siegfried 2015; Picault 2019). These tools can be grouped into four different categories based on their major objectives: (1) "To promote communication and/or facilitate the exchange of information," (2) "To provide cognitive support for learners," (3) "To facilitate information search and retrieval," and (4) "To enable or enhance content presentation" (Schmid et al. 2014, p. 274). Although the use of these tools is even more prevalent than teaching an entire course online, the evidence on the effectiveness of these tools is mixed. Schmid et al. (2014) found that online tools offering students active engagement opportunities via cognitive support tools yielded the largest average effect size in student achievement, although heterogeneity in outcomes persisted. Examples of these types of tools include concept maps, simulations, wikis, different forms of elaborate feedback, spreadsheets, and word processing exercises. Although online posting of presentation tools might not have a large effect on student achievement, Borokhovski et al. (2016) found that technology-supported student-to-student interactions improved student learning significantly. Finally, Allgood et al. (2015) provide a summary of studies that address the use of online learning in economics classes. They conclude that online courses have worse learning outcomes, even after controlling for student selection. However, they also suggest that in cases where studies find no difference in outcomes (e.g., completing homework online or on paper), there may be an opportunity for instructors to adopt these as labor-saving innovations.

In summary, simply *adopting* online tools for teaching will not necessarily improve and in some cases may even worsen learning outcomes. The use of online technology needs to be purposefully *designed* and *well-integrated* with other aspects of the course and the overall learning objectives. Although some tools can be viewed as labor-saving technologies and serve as substitutes for faculty involvement, many will likely have greater benefits for students when we treat them as complements rather than substitutes to student-faculty interaction. Below, we provide three examples of innovative uses of online tools by instructors teaching in undergraduate agricultural and applied economics programs.

3.1 Interacting with Agricultural Policy—The Use of Twitter to Stimulate Student Interest and Engagement

Julianne Treme uses Twitter as a pedagogical tool to promote higher levels of thinking in both her Introduction to Economics course and 400-level Agricultural Policy course taught in the Department of Agricultural and Resource Economics at North Carolina State University. Her goal was to have students actively engage with agricultural policy by creating tweets that relate to current events and her course material. Students were asked to select an agricultural leader/organization for the assignment. They created a private account with an instructor-approved handle and tweeted a predetermined number of times per week over a series of weeks. Treme notes that the assignment can be varied depending on the length of the course/unit. For example, a student in the 400-level policy course is required to tweet a minimum of three times a week for 11 weeks. Students in an introduction to economics course are required to tweet over a shorter number of weeks to satisfy a specific class unit requirement. Each class selects a profile picture/banner to display on all Twitter accounts associated with the project and a class hashtag to easily track all course tweets. The assignment counts for between 8 and 15 percent of their final grade, depending on the length of the project, and serves as a creative alternative to a more traditional policy paper.

One of the key aspects of this assignment is that students are instructed to construct tweets from their leader/organization's perspective. They also have to be related to the course material and current events, and include links to relevant articles. Students are required to interact with other students by providing thoughtful replies to their peer's tweets on a weekly basis. This assignment therefore engages students in higher-order thinking. It works because students are not expected to respond with the "right" answer; they are extending course information as it applies to their knowledge of their leader/organization to address current events in an original way. As a result of the tweets, students develop a repository of resources that can be discussed in class.[10] The rubric Treme created provides clear guidance and outlines exemplary work related to content, interaction with classmates, and course themes. It is included in the appendix for additional context and grading. The instructor requirements associated with this assignment are: (1) initial setup of approved leaders/organizations, (2) monitoring the content of tweets, and (3) grading the tweets based on the rubric. Compared to traditional assignments, the overall time required for this assignment was similar, while the benefits to both students and the course are greater. This assignment has generated increased engagement in the classroom, greater general interest in course material, and more analytical short answer responses. Student feedback has been positive, as students have noted that they enjoyed completing this project because it was a different way to demonstrate their knowledge and a fun way to engage with the class. Students also noted that the Twitter assignment led to a deeper understanding of the material in class because they had real time examples with which to connect. Feedback frequently mentions that the shortened character requirement for tweets makes the project manageable, easier to fit in their schedule, and a great way to keep up with current events.

[10] Treme also created Twitter polls she uses as a class starter.

3.2 Use of Diverse Student Evaluation Tools

Luis Peña-Lévano teaches Quantitative Methods in Food and Resource Economics (FRE) online. This is an undergraduate, mathematic intensive core class for the FRE major, offered every semester. As the sole instructor, he imparts this course to all locations of the University of Florida. It is divided into 10 units (i.e., topics involve matrix algebra, multivariate calculus and optimization, linear programming, and integration), each of which are accompanied by an online pre-recorded lecture. To overcome the challenge of teaching mathematical tools in an online platform, he initially implemented four techniques.

Peña-Lévano's first two implemented learning tools are designed to incentivize students to watch the video lectures: (1) *Pre-labs are* a short assignment of practical problems for which solutions are included in the video lectures. (2) *Quizzes* consist of two to three questions based on similar questions to the pre-labs. These graded small tasks allowed students to gain a better understanding of where they needed to focus their efforts when studying. In addition, it allowed Peña-Lévano to detect areas for improvement. He was able to provide additional examples for a challenging unit before homework assignments were due.

Two additional approaches addressed student and instructor interactions: (3) *In-person Computer Lab Sessions* were hosted by teaching assistants, and attendance was optional. For instance, one of the units involved the use of Excel to solve mathematical problems. Students can directly address any concerns regarding software compatibility or any doubt in how to create simulations. They were able to go over examples presented in the video lectures in person. (4) *Review Sessions* were held by Peña-Lévano every two or three weeks. He directly addressed any questions students had and went over additional exercises to reinforce the learning experience. On average, 50 to 80 percent of the classes attended these sessions. While these innovations required additional time commitments, they have paid off. Learning outcomes have improved. In the course evaluations, students reported that the class is engaging and that the instructor is involved in the learning process.[11]

Peña-Lévano continues to add additional techniques. They include a *Final Mini-Project*, which is a special assignment where students needed to create a short practical problem based on one of the units of the class. It helped students to better understand the topics and use the mathematical tools and principles learned during the course to create a new problem.

3.3 Adoption of *Packback*, an AI-Assisted Discussion Board Tool

Discussion boards can provide students with the opportunity to engage with material outside of class and build on concepts they've learned in class in more open-ended and creative ways than quantitative assignments (e.g., problem sets) may allow. One new tool in the discussion board space is *Packback*.[12] This discussion board tool asks the question "What are you curious about?" Students are thus prompted to post open-ended questions, and an AI-assisted tool gives students real-time feedback on their questions. For example, if a question is too short, not open-ended or does not include a citation, the student will be prompted to edit it in real-time. The AI (or a peer or instructor) can also flag questions, and staff at *Packback* will follow up to provide guidance to the student. Peers can respond to questions and "spark" questions or responses that they find interesting, with the number of sparks serving as an indicator to an instructor of student interest in that discussion. Instructors can "pin" a question to the top of the question list or star questions to create a curated list to prompt students to engage on specific topics or to highlight exemplary questions. Instructors also have the ability to coach or praise a student and provide specific feedback on a student's post. The tool further provides an algorithm-based "curiosity score" for each student's question. This score is based on question length, use of sources and links, and readability of text. It is intended to serve as a proxy for the quality of the student's post. The built-in gradebook tool then allows the instructor to grade students by curiosity points or simple participation.

[11] Further details on these innovations can be found in a recently published article (Peña-Lévano 2020).
[12] Interested readers may learn more about this tool at: https://www.packback.co/.

Zoë Plakias and her colleague Anna Parkman recently began using *Packback* for classes offered in the Department of Agricultural, Environmental, and Development Economics at Ohio State University. Plakias adopted *Packback* in a large in-person introductory microeconomics course in the Spring of 2019. Students were required to post one question and two responses weekly. She required that questions be related to the current or previous week's class topic, and posting of questions accounted for up to 10 percent of the total course grade, based on simple participation. Exemplary questions and interesting topics raised on *Packback* were highlighted weekly in class, and posts that revealed poor understanding of concepts across many students motivated in-class clarifications of that material.

Plakias found that students engaged in vibrant discussions online on a variety of topics and shared personal stories and interests that allowed her to better tailor lectures to student interests and needs. Students also appreciated the opportunity for graded low-stakes assignments. However, she also observed significant heterogeneity in the quality of posts, with the AI unable to detect some aspects of quality. For example, incorrect statements about economics or questions with answers that could be found in the lecture slides or textbook were not flagged and were not reflected in the post's "curiosity score" and because of the large class size (125), students sometimes had difficulty providing original questions or responses. Low quality questions went unanswered entirely. In addition, the cost ($25 per semester) left some students dissatisfied, as they did not see the added value relative to the built-in discussion board tool in Ohio State's learning management system provided by Canvas.

Although the platform was relatively easy to use and its real-time prompts to students can function as a labor-saving mechanism for faculty, getting the most out of a discussion board still requires significant management time on the part of instructors. It remains somewhat unclear to what extent *Packback* actually lowers overall management time. The single best innovation of *Packback* appears to be the prompt—it encourages student-centered learning by incentivizing students to ask questions related to the class material and allows them to direct their own learning. In conclusion, Plakias suggests comparing the functionality of any built-in discussion board tools within your university's learning management system with *Packback* to ensure the benefits are worth the costs to students.

4 Conclusions

Enrollment in higher education has increased across all populations. Many undergraduate programs have started to move courses online and encourage the use of technology and online tools. The rapid move to remote instructions as an emergency response to the Covid-19 pandemic and social distancing requirements will likely accelerate these changes in the teaching and learning environment. However, these developments raise important questions regarding the quality of teaching. This article wants to encourage a thoughtful discussion of necessary innovations and provide useful tips for instructors looking to increase their teaching effectiveness in large undergraduate classes whether content is delivered online or face-to-face.

We started a discussion of how to increase student engagement and adequately prepare students for the many job opportunities in agriculture-related sectors with an organized track session at the 2019 AAEA Annual Meeting. Student engagement can be defined as a dynamic process that combines behavioral, cognitive, and emotional dimensions of learning, results in higher levels of academic achievement, and motivates students to develop life-long, self-regulated, and active learning behaviors. As a discipline, it is further essential that we attract and retain talent to careers in agriculture to be able to address the many challenges posed by labor shortages, supply chain management issues, international trade, climate change, demands for transparency, as well as overall health and environmental concerns.

The economic situation has changed dramatically since the beginning of the COVID-19 pandemic. While the downturn might affect agricultural-related sectors relatively less dramatically than other areas of the economy, new challenges will surely arise. Many of us already needed to respond quickly and not only adjust in our personal lives but also our teaching approaches. These new demands served as a powerful reminder that the development of teaching innovations can be time-consuming, and that the implementation of ideas does not always go as planned. Student-centered learning and teaching approaches require a continuous commitment and can greatly benefit from an ongoing exchange of effective practices. We hope that by sharing purposefully designed teaching innovations and thoughtful usage of online and social media tools, we will inspire teaching scholars, faculty, and graduate students to join in our efforts to continuously design and redesign classes and curricula to better serve our students.

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Appendix: Twitter Grading Rubric

Element	Exemplary 10	Proficient 8	Partially Proficient 6	Unsatisfactory 2	Points Earned	Possible Points
Reflects Course Themes (Points x2)	The themes, ideas, and essential questions for the class are reflected in tweets. Excellent demonstration of knowledge of course content.	The themes, ideas, and essential questions for the class are reflected in most tweets but not all. Good demonstration of knowledge of course content.	The themes, ideas, and essential questions for the class are represented in less than half of the tweets and/or course content is poorly demonstrated.	No themes, ideas, or essential questions are represented in the tweets.		**20**
Content	Tweets are creatively and succinctly written to stimulate dialogue and commentary. The leader's voice and attitude are reflected in the tweets.	Most tweets are written to stimulate dialogue and commentary. Leader's voice and attitude are reflected in most tweets but not all.	A few tweets are written to stimulate dialogue and commentary. Leader's voice and attitude are reflected in some of the tweets.	Tweets are poorly written and do not stimulate dialogue and commentary. Little understanding of leader and/or leader's attitude not reflected in tweets.		**10**
Interaction Quality with Classmates	Interactions consistently provide meaningful addition to the class discussion such that interactions lead to additional tweet conversations from other classmates.	Interactions with other leaders provide a meaningful addition to the class discussion.	Some interactions and responses to tweets are negative and disrespectful, and/or interactions provide little value to the discussion.	Few interactions with other leaders and/or interactions to tweets are negative and disrespectful, and provide no value to the discussion.		**10**
Total Tweets and Frequency	Creates and sends tweets more frequently than required. (Total tweets exceeds 20 and at least 5 tweets weekly. No retweets.)	Creates and sends tweets as often as required. (Total tweets equal 20 and 5 tweets weekly. No retweets.)	Creates and sends tweets somewhat less often than required. (Total tweets between 15 and 19 and misses one week of tweeting or tweets less per week than required.)	Creates and sends tweets too infrequently to meet the requirements. (Total tweets less than 15 and/or misses two or more weeks).		**10**
Mechanics	N/A	Writes with no errors in grammar, capitalization, punctuation, and spelling.	N/A	Writes with numerous major errors in grammar, capitalization, punctuation, and spelling. (More than 5 errors per tweet).		**8**
				Points		**58**

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Teaching and Educational Methods

Gold in Them Tha-R Hills: A Review of R Packages for Exploratory Data Analysis

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Abstract
With an accelerated pace of data accumulation in the economy, there is a growing need for data literacy and practical skills to make use of data in the workforce. Applied economics programs have an important role to play in training students in those areas. Teaching tools of data exploration and visualization, also known as exploratory data analysis (EDA), would be a timely addition to existing curriculums. It would also present a new opportunity to engage students through hands-on exercises using real-world data in ways that differ from exercises in statistics. In this article, we review recent developments in the EDA toolkit for statistical computing freeware R, focusing on the tidy verse package. Our contributions are three-fold; we present this new generation of tools with a focus on its syntax structure; our examples show how one can use public data of the U.S. Census of Agriculture for data exploration; and we highlight the practical value of EDA in handling data, uncovering insights, and communicating key aspects of the data.

1 Introduction

There's gold in them thar hills! —Mark Twain in The American Claimant

A hundred seventy years ago Americans flocked to California in search of gold. The Gold Rush left the country with a powerful image of massive realignment of capital and labor in search of new economic opportunities. With each subsequent era came new manifestations of the Gold Rush in the form of booming industries, invoking a sense of new, ground-breaking opportunities that could lead to permanent structural change in the existing business environments. Today, businesses are gathering and accumulating an enormous amount of data: effective goldmines. In this new Gold Rush, the demand for the skills to understand, explore, and apply data is accelerating. Computer programmers and data scientists are particularly in high demand, and their tool kit is expanding rapidly. In preparing students for an increasingly data-driven world, applied economics programs have an increased role to play through teaching data literacy and modern data analytics skills.

A good starting point may be to teach relevant tools of data exploration and visualization, also known as exploratory data analysis (EDA), that are popular in the field of data science. The exploratory nature of EDA contrasts with statistical modeling and hypothesis testing, a long-standing tradition in modern economics curriculums. An increasing number of economics courses integrate statistical programming in R as an integral topic. Current examples include Microeconomics with R by John Humphries at Yale University, Methodology of Economic Research by Jude Bayham at Colorado State University, econometrics course materials taught with R by Ed Rubin, Data Science for Economists by Grant

McDermott at University of Oregon, and Applied Econometrics by Taro Mieno at University of Nebraska–Lincoln as far as the authors are aware of. Indeed, the tools of EDA are generally complementary to the teaching of analytical skills and thought processes emphasized in applied economics. Teaching EDA tools would be not only timely but also stimulating for students who have an interest in learning to use real-world data on current socioeconomic issues. Hands-on EDA exercises can provide a vital opportunity for students to acquire practical data analysis skills beyond the usual exercises in statistics.

In this article, we review recent developments in the EDA toolkit in statistical computing freeware R. Our intended audience includes course instructors, graduate students, and advanced undergraduate students particularly those who are pursuing independent studies, participating in research projects, or serving as teaching assistants. We use data sets familiar to agricultural economists for illustration. Our contributions are three-fold: we present this new generation of tools with a focus on its syntax structure, our examples show how one can use public data of the U.S. Census of Agriculture for data exploration, and we highlight the practical value of EDA in handling data, uncovering insights, and communicating key aspects of the data. Our review focuses on the tools of the `tidyverse` package, a meta package that includes *ggplot2* and *dplyr* and uses a streamlined coding syntax across its member packages (Wickham et al. 2019).[1] In writing this article, we borrow core concepts from **R for Data Science** (Wickham and Grolemund 2017). For interested readers, additional resources include **ModernDive** (Ismay and Kim 2019), **Data Visualization with R** (Kabacoff 2018), **Data Visualization: Practical Introduction** (Healy 2018) and **Geocomputation with R** (Lovelace, Nowosad, and Muenchow 2019).[2] All R code used in this document is made available in the supplementary appendix.[3]

The rest of the article is organized as follows. We provide a short, general comparison between R and Stata, a popular proprietary statistical software among economists. The main contents of our review of R tools consist of four sections that (a) introduce core data visualization methods of *ggplot2*, (b) demonstrate the application of data transformation methods of *dplyr* with U.S. agriculture data, (c) provide an analytical example within a data exploration narrative, and (d) briefly describe additional tools. The final section concludes the article.

2 Comparison of R and Stata

As a general comparison, we comment on the relative strengths and weakness of two commonly used software programming languages in the field of economics, R and Stata.[4]

2.1 A Basic Introduction

R, formally known as *R Projects*, is a statistical computing, graphics, and programming language that is available free of charge. R is not managed by a single person or company but instead by an "R core group."[5] The R core group has the authority to modify the R source code archive. For most users, it suffices to know that R simply executes commands according to programs, or R functions, that are loaded by default and by the user. To execute commands beyond basic computations and visualization tasks, R users need to load R packages, collections of R functions developed and shared by other R users. Which packages to use depends

[1] They are not part of the base package. To install a R package, execute the code in the R console, for example: `install.packages("tidyverse")`.

[2] R for Data Science: https://r4ds.had.co.nz/, ModernDive: https://moderndive.com/, Data Visualization with R: https://rkabacoff.github.io/datavis/, Data Visualization A Practical Introduction: http://socviz.co/index.html, Geocomputation with R: https://geocompr.robinlovelace.net/.

[3] https://github.com/tmieno2/R-AETR

[4] Software download: https://cloud.r-project.org/ and https://download.stata.com/download/.

[5] https://www.r-project.org/contributors.html.

on the user's objectives and personal preferences. For example, two popular EDA toolboxes are the *tidyverse* package, which is our focus in this article, and the *data.table* package.

Stata is a proprietary statistics software from StataCorp. In most universities, students can access Stata in their computer labs through a site license. As of December 2019, the Stata perpetual license for U.S. students is $225 for Stata/IC (the least powerful version), $425 for Stata/SE, $595 for Stata/MP 2-core (midrange capabilities), and $795 for Stata/MP (the most powerful). Short-term U.S. student licenses are also available for $48 for Stata/IC and $125 for Stata/SE for 6 months. StataCorp is responsible for software descriptions, updates, and additions of Stata commands. Separately, some user-contributed Stata packages, a collection of Stata *ado* files, are available through RePEc (which stands for Research Papers in Economics). Also, StataCorp maintains a quarterly publication of the Stata journal for user-contributed statistical techniques and effective teaching methods using Stata.

2.2 Statistical Capability

R is open-source software with a rapidly expanding toolkit built by the R user community across diverse fields of statistics and sciences. The R toolkit includes advanced tools of machine learning, Bayesian statistics, and spatial statistics that are of interest to many economists, as well as statistical tools in other disciplines like biostatistics that may help economists working on interdisciplinary research. R offers rich tools in some fields of econometrics, including, for example, linear or quadratic programming (*Rglpk* and *ipotr* packages), nonlinear optimization (*nloptr* package), and advanced quantile regression analyses (*quantreg*, *quantreg.nonpar*, and *bayesQR* packages).

Stata's development of new tools primarily rests on StataCorp's undertaking. Given its limited resources, the company focuses on tools for social scientists, including economists. For instance, Stata offers a variety of estimation options for state-of-the-art treatment effects and panel data estimation techniques that are useful to economists. Advanced coding implementation of customized nonlinear estimation is also available.[6] The documentation of various commands in Stata is consistently managed by the company and hence user-friendly; in contrast the user-contributed projects of R may lack consistent documentation or transferable command syntaxes across various packages. Thus, a familiarity with both R and Stata would give the user access to a wide range of statistical methods, some of which may be available in one software but not in the other.

2.3 Machine Learning Methods

There is a growing interest in R among agricultural economists, and it can be explained by the increased importance of Big Data and the expanding capabilities of machine learning methods (Coble et al. 2018; Storm, Baylis, and Heckelei 2019). Numerous packages that implement state-of-the-art machine learning methods are available in R, including LASSO, Random Forest, Neural Network, and Boosted Regression. The *keras* and *tensorflow* packages handle Convolutional Neural Network (CNN), a workhorse for image processing used in facial recognition and autonomous driving. An interesting application of CNN may include spatial data analysis (Storm, Baylis, and Heckelei 2019). The *rnn* package allows for recurrent neural network modeling, which is particularly suitable for state-dependent time-series analysis and a certain type of price analysis. The *grf* package leads the generalized random forest framework, which includes causal forest, quantile forest, and instrumental forest developed by Athey, Tibshirani, and Wager

6 https://blog.stata.com/2016/01/26/programming-an-estimation-command-in-stata-a-review-of-nonlinear-optimization-using-mata/

(2019). The *XGBoost* package offers extreme gradient boosting regression, which has been shown to outperform other machine learning methods in many applications.

In the latest version of Stata 16, StataCorp has introduced LASSO commands. In addition, user-contributed packages such as *LASSOPACK* (LASSO, elastic net, and ridge regressions), *RFOREST* (random forest classification and regression), and *KFOLDCLASS* (K-fold cross-validation for binary outcomes) are available. It is plausible that many machine learning algorithms will be gradually made available.

2.4 Spatial Data Handling

Many data analyses in agricultural economics involve spatial considerations. R offers an extensive capability in processing spatial data (*sp*, *sf*, *raster*, *rgdal*, and *rgeos* packages are some examples) and creating geographical maps (*ggplot2* and *tmap* packages have wide use). If for instance, one is interested in understanding the impact of climate on cropping patterns at the sub-county level, he or she could combine the Cropland Data Layer (CDL) files and the county boundaries data to summarize a mixture of cropping patterns for each county, all of which can be done within R without having to use specialized programs such as ArcGIS or QGIS.[7] In contrast, Stata has a very limited capability for handling spatial data or generating geographic data figures. One exception may be the user-contributed mapping commands like *spmap* and *maptile*.

2.5 Publicly Available Data

Recent developments in R include packages that are dedicated specifically for downloading publicly accessible data. One can download data from the USDA NASS CDL (*cdlTools* package), USGS and EPA hydrologic and water quality data (dataRetrieval), Quick Stats (*rnassqs* package), PRISM (*prism* package), Daymet (*daymetr* package), Sentinel-2 satellite imagery data (sen2r package), the National Elevation Data Set digital elevation models, the NCSS Soil Survey Geographic data set, and many others (*FedData* package). These R packages can automate the process of manually downloading individual public data files. Additionally, the *httr* package allows for data requests via Application Programming Interface (API), and the *jsonlite* package helps process JSON data files that are common in API outputs. Stata has a capability to utilize API through the *winexec curl* command. Also, downloaded data in XML or JSON format can be imported into Stata via *xmluse* or *insheetjson*, respectively.

3 Data Visualization with *ggplot2*

This section highlights simple data visualization methods with R's *ggplot2* package for creating scatter, line, and bar plots.[8] The *ggplot2* syntax has three essential components for generating data plots: *data*, *aes*, and *geom*. It implements the following philosophy:

A statistical graphic is a mapping of ***data*** *variables to* ***aesthetic*** *attributes of* ***geometric*** *objects*.
(Wilkinson 2005, p. 42)

where the data, aesthetic attributes, and geometric objects are programmed as follows:

- *data*: a data frame; e.g., the first argument in *ggplot(data, ...)*.

[7] For example, see R as GIS for Economists: https://tmieno2.github.io/R-as-GIS-for-Economists/.

[8] For basic R tutorials, try http://www.cookbook-r.com/ or https://en.wikibooks.org/wiki/R_Programming/Sample_Session. A useful material for teaching may be https://psyteachr.github.io/.

- *aes*: *x* and *y* variables specifying the horizontal and vertical axes and other variables by which data can appear in different colors, shapes, sizes, etc.; e.g., *aes(*x = *var*_x, y = *var*_y, *color* = *var*_z*)*.
- *geom*: geometric objects such as points, lines, bars, etc.; e.g., *geom_point()*, *geom_line()*, *geom_bar()*, *geom_histogram()*.

This simple philosophy provides an easy way for remembering how to relate the three components with each other in coding. Note that data sets are often referred to as data frames, corresponding to R's *data.frame* class objects that, unlike matrix class objects, can contain both string and numeric variables in columns.

We now examine some basic examples. The following code produces scatterplots of horsepower and miles per gallon using the *mtcars* data set, a sample data set automatically loaded in *base R* (Figure 1). It came from the 1974 Motor Trend U.S. magazine and contains 11 automobile specification attributes for 32 cars, including attributes like gross horsepower (hp), miles per gallon (mpg), number of cylinders (cyl), automatic transmission indicator (am), and weight in 1,000 of pounds (wt).[9]

```
# scatterplot of hp and mpg
ggplot(mtcars, mapping = aes(x = hp, y = mpg)) +
  geom_point()

# convert variable cylinder into a categorical variable
mtcars$cyl <- as.factor(mtcars$cyl)

# scatterplot with added color and shape by cylinder
ggplot(mtcars, mapping = aes(x = hp, y = mpg, color = cyl)) +
  geom_point(aes(shape = cyl))
```

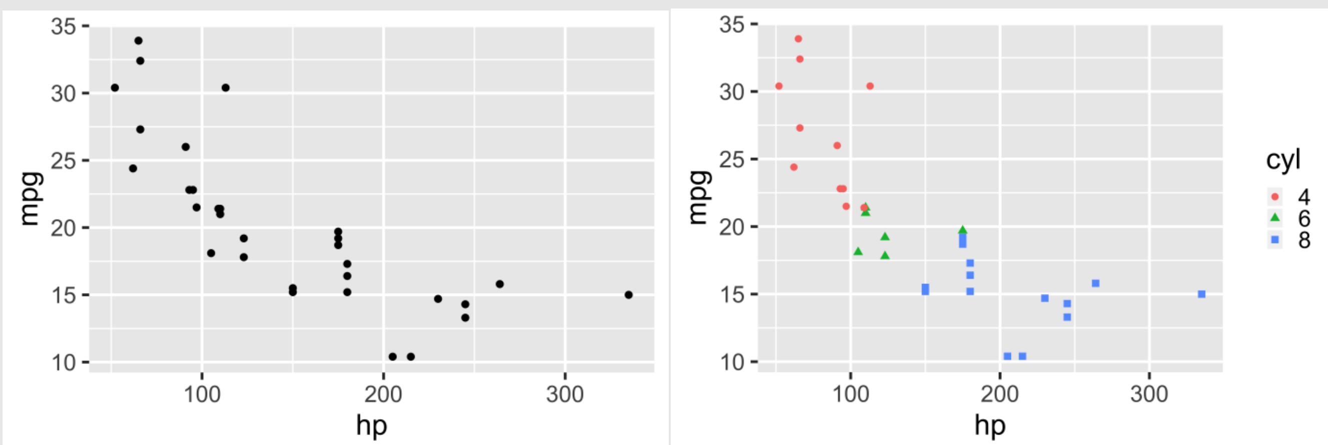


Figure 1. Example of Scatterplots Using the mtcars Data Set in Base R

In the next example, we add more layers of geometric objects, see bullet point "geom" above (Figure 2). By default, a geometric object inherits the aesthetic attributes specified in *gglot(data, aes())*. To change those attributes, one needs to provide specific attributes for each geometric object. In the first two plots, note that the presence or absence of a color attribute specification in *ggplot(data, aes())*, which implies different color attribute specifications in *geom_smooth()*. The third plot contains an example of fixed aesthetic attributes like color and point size that are specified outside *aes() and hence* do not depend on

[9] While unrelated to agriculture, this data set is commonly used for basic R tutorials and hence good to be familiar with.

the data. Also, one can add a geometric object with a new data set. For example, the third plot contains a geometric object based on a subset of the data.

```
# add a layer of linear regression model fit for each cylinder type
ggplot(mtcars, aes(x = hp, y = mpg, color = cyl)) +
  geom_point(aes(shape = cyl)) +
  geom_smooth(method = lm)

# add a layer of smooth regression fit (locally estimated scatterplot
smoothing: loess) across all cylinder types
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  geom_smooth()

# add a layer of large yellow dots to indicate automatic transmission
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(data = filter(mtcars, am == 0), color = "yellow", size = 5) +
  geom_point(aes(shape = cyl, color = cyl)) +
  geom_smooth()
```

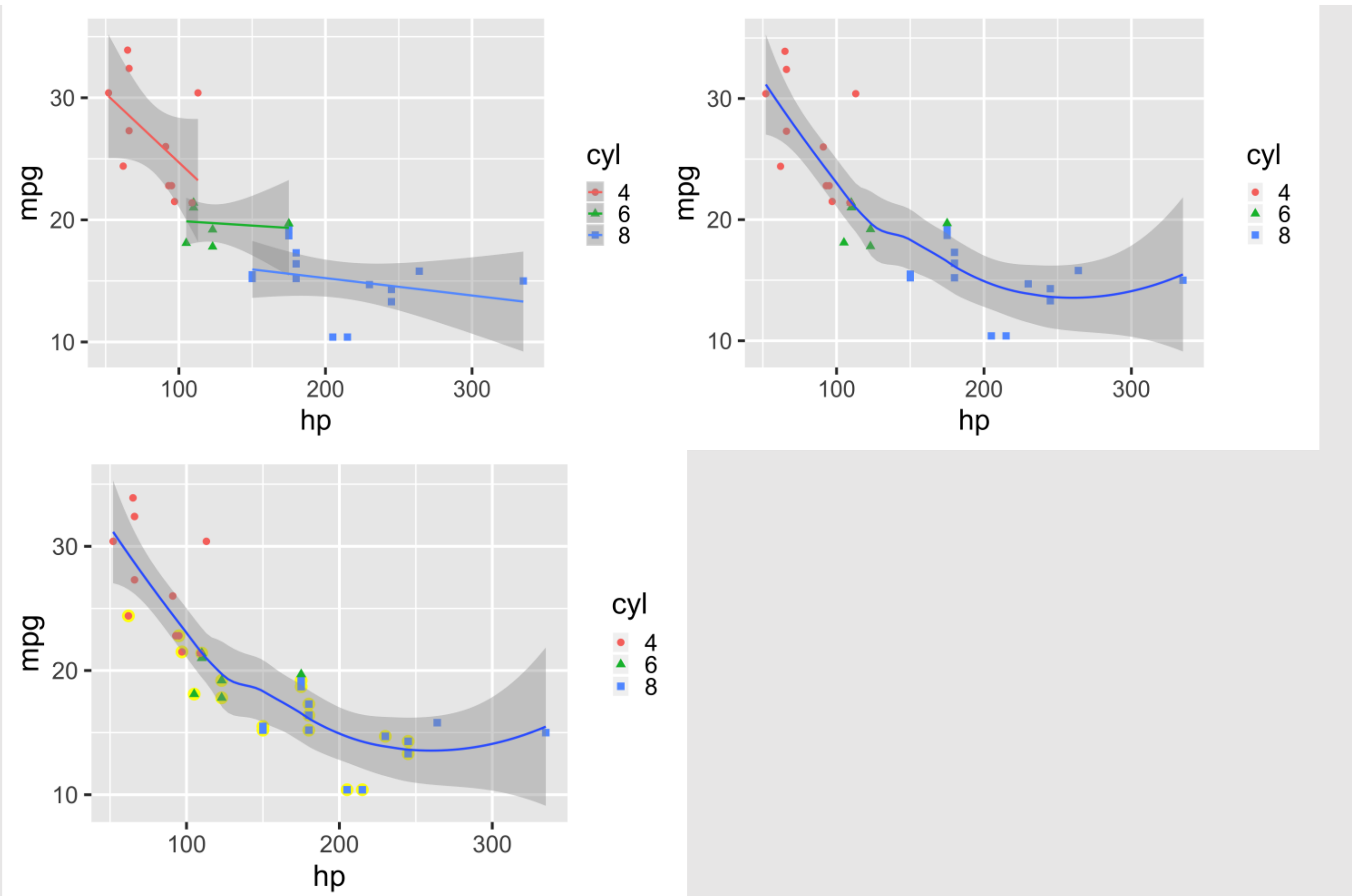


Figure 2. Example of Scatterplots with Linear Model and Smooth Fits Using the mtcars Data

Additionally, a *facet_wrap()* or *facet_grid()* layer splits the data into subsets by a categorical variable(s) and generates multiple data plots on those subsets (Figure 3).

```
# add a character variable for transimission type
mtcars$am_char <- recode(c(mtcars$am), "0" = "automatic", "1" = "manual")

# plot subsets of data by transmission type
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  facet_wrap( ~ am_char)

#  plot subsets of data by transmission type and number of gears
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  facet_grid(gear ~ am_char)
```

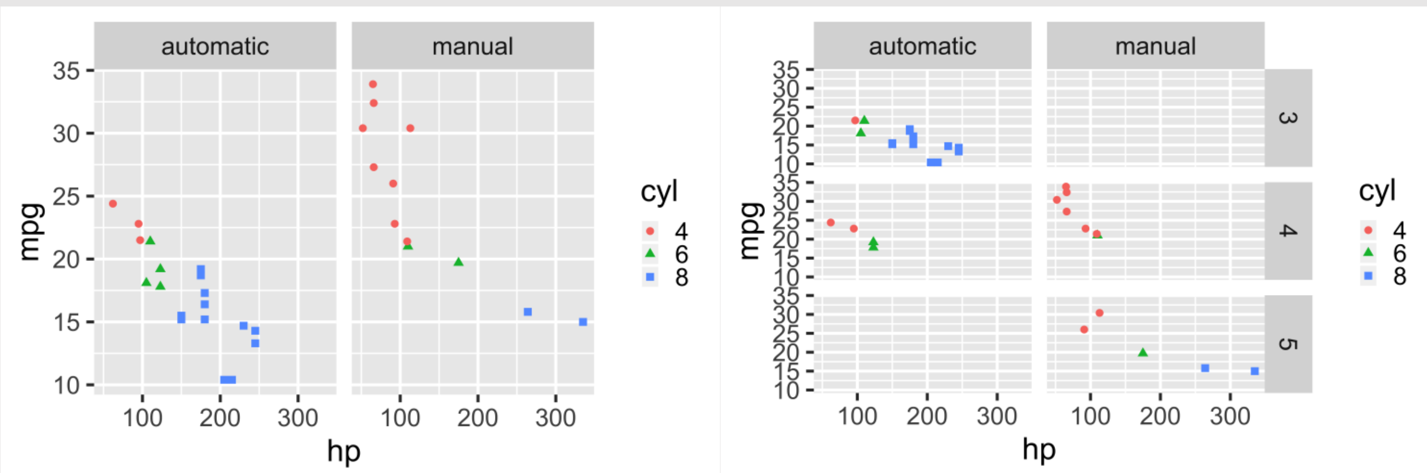


Figure 3. Example of Scatterplots for Subsets of the mtcars Data
Note: The data are split into two subsets by transmission type (top) and six subsets by the combination of transmission type and number of cylinders (bottom). Variables mpg, hp, and cyl refer to miles per gallon, horse power, and the number of cylinders, respectively.

Various cosmetic adjustments can be controlled through additional layers of coordinate attributes (scale and coord) and other graphics attributes (labs, theme, and guides) as demonstrated in Figure 4.

```
# change the displayed values on the y axis
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  scale_y_continuous(breaks = seq(10, 36, by = 4))

# map in log10 scale
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  scale_x_log10() + scale_y_log10()

# change theme to black and white and overwrite axis labels
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  theme_bw() + labs(x = "Horse power", y = "Miles per gallon")

# overwrite the *joint legend* for color and shape attributes
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  guides(
    color = guide_legend(title ="cylinder", override.aes = list(size = 4)),
    shape = guide_legend(title ="cylinder", override.aes = list(size = 4))
    )
```

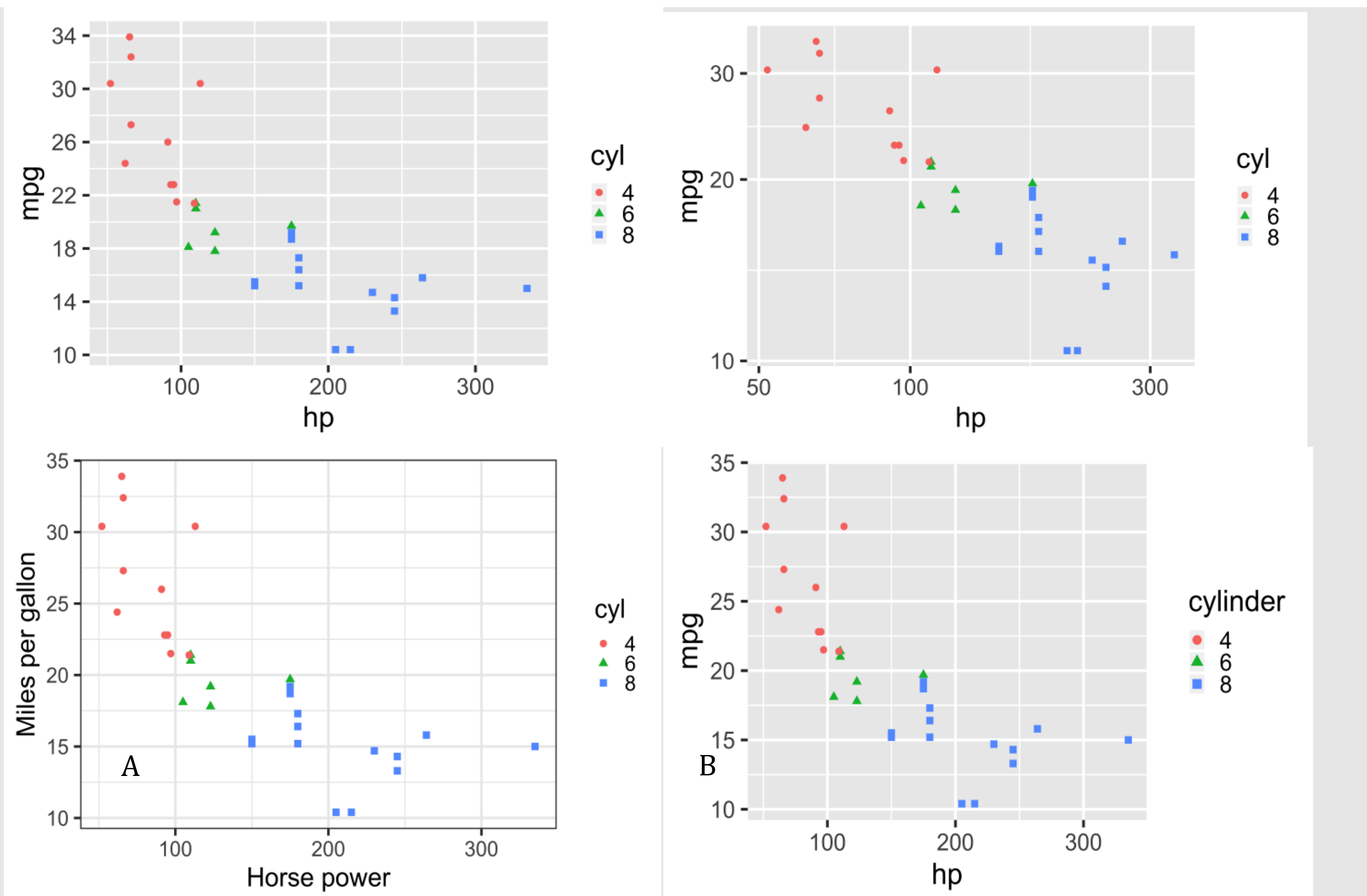


Figure 4. Example of Scatterplots Using the mtcars Data with Cosmetic Adjustments

Notes: (A) Specified breaks on the *y* axis, (B) log-scaled axes, (C) added axis labels and a black-and-white theme, and (D) enhanced legend keys.

The next set of figures provides examples of adding a data label layer (Figure 5) and examples of histograms and bar plots (Figure 6).

```
mtcars$car_model <- rownames(mtcars)

# add labels of car model for cars that have either hp > 200 or mpg > 25
ggplot(mtcars, aes(x = hp, y = mpg)) +
  geom_point(aes(shape = cyl, color = cyl)) +
  ggrepel::geom_label_repel(aes(label = car_model),
                            data = filter(mtcars, hp > 200 | mpg > 25))

# example of boxplot
ggplot(mtcars, aes(x = am_char, y = wt)) +
  geom_boxplot() +
  geom_label_repel(aes(label = car_model),
                   data = filter(mtcars, wt > 4.5 | wt < 3, am == 0))
```

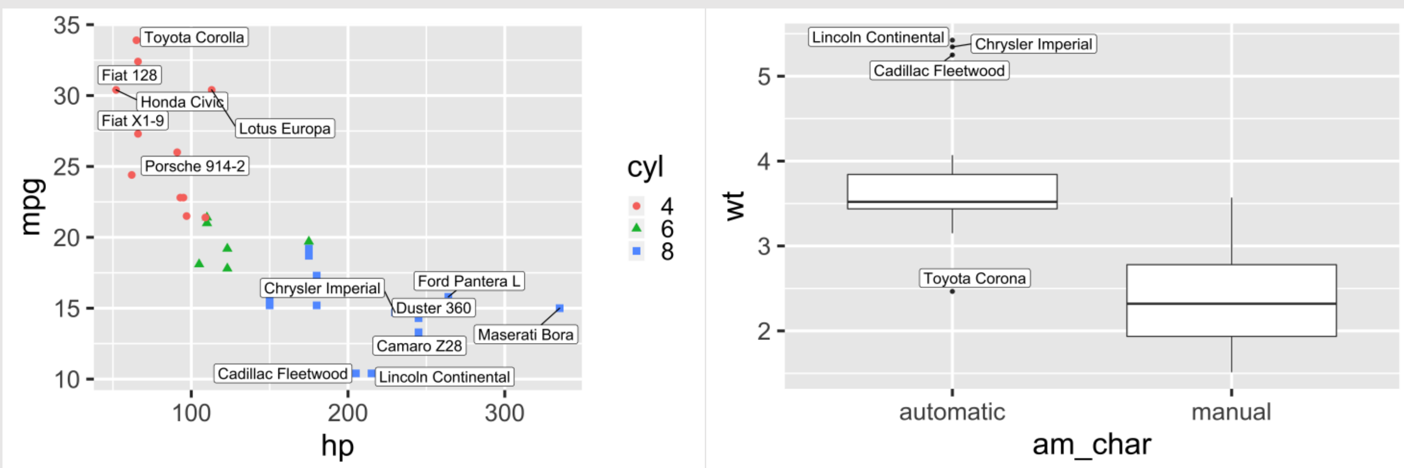


Figure 5. Example of Plots Using the mtcars Data with Selected Data-Point Labels

```
# examples of histograms
ggplot(mtcars, aes(x = wt, fill = am_char)) +
  geom_histogram(binwidth = .75)

ggplot(mtcars, aes(x = wt, color = am_char)) +
  geom_freqpoly(binwidth = .75, position="dodge", size = 2)

# examples of barplots
ggplot(mtcars, aes(x = cyl, fill = am_char)) + geom_bar()
ggplot(mtcars, aes(x = cyl, fill = am_char)) + geom_bar(position = "dodge")
ggplot(mtcars, aes(x = cyl, fill = am_char)) + geom_bar(position = "fill") + labs(y = "fract
ion")
```

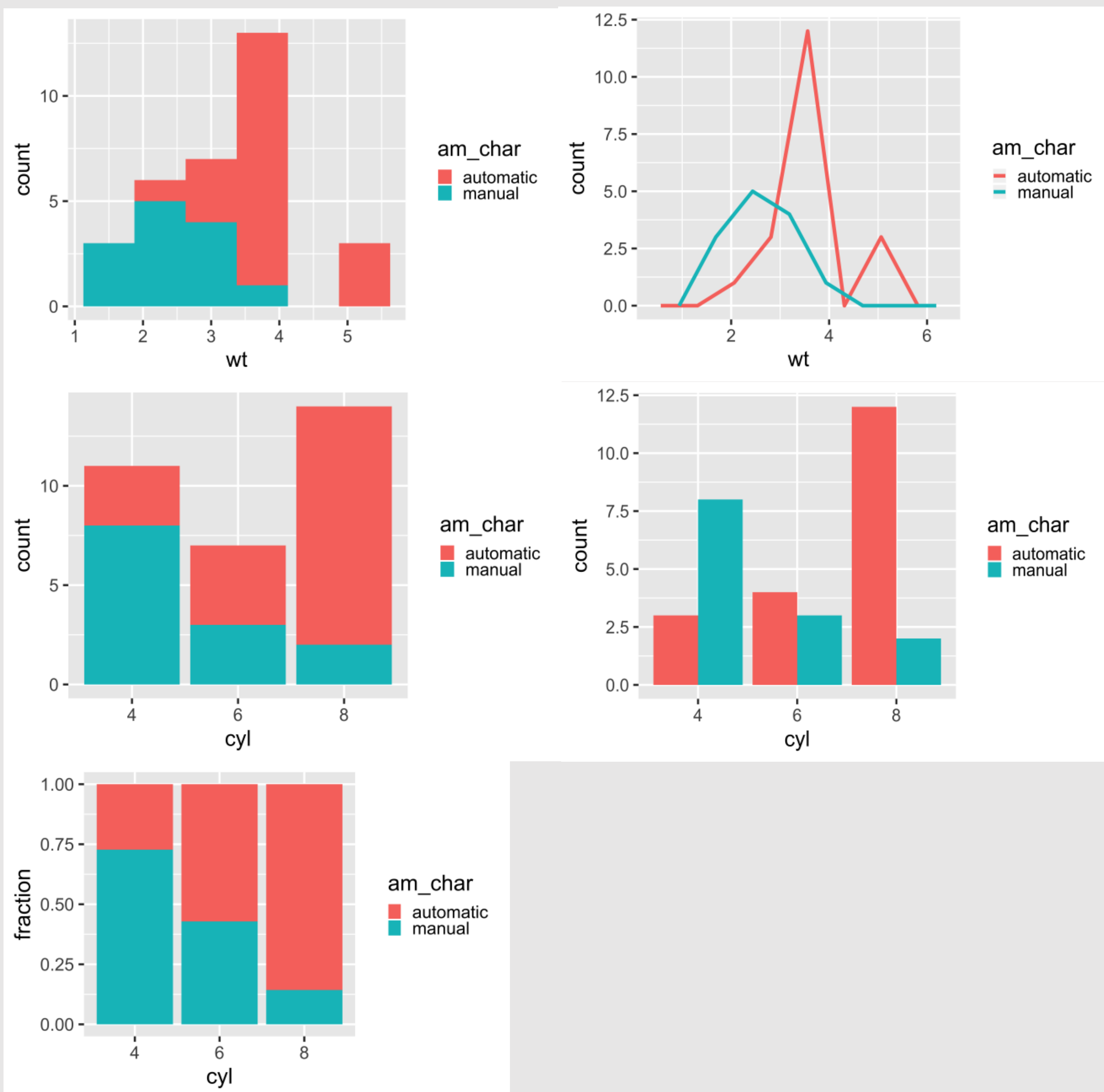


Figure 6. Example of Histograms (Classic Compound Bars and a Line Plot Style) and Bar Plots (Three Examples) Using the mtcars Data

Variables wt, cyl, and am_char refer to weight, the number of cylinders, and transmission type, respectively.

4 Data Exploration with *dplyr*

This section reviews essential functions for transforming data with **dplyr** and uses U.S. agriculture data for a demonstration of EDA that includes querying data, applying geospatial visualizations, and visual presentations of data summaries. Before we begin, let us note why exploring data is important and why tools of data transformation matter. Most statistical tools allow us to transform a data set by creating new variables, selecting specific subsets, sorting or grouping data, collapsing data into group-level statistics, or any sequential combination of those operations. And perhaps when combined with some data visualization, often by chance, the transformed data set may reveal new aspects of the data.

While curiosity-based exploration may seem like a luxury, it is necessary if we want to understand the data and discover the insights it provides. Only after a particular combination of data transformations, may certain aspects of the data be revealed or become noticeable. That should prompt subsequent questions like, "How do we know which data transformations to perform?" or "How can we tell whether we have uncovered all possible interesting aspects of the data?" A simple answer to both questions is, "We don't, but we should try our best." This is precisely why the tools of EDA matter. The easier and the simpler the tools are, the more frequently we use them and the more thoroughly we explore the data. The power of data visualization is multiplied by the ability and agility to transform the data at hand.

The tools of the *dplyr* package enable us to act nimbly, explore, and understand the data. That can make us feel like we are interacting with the data rather than merely transforming it. Before discussing why that may be the case, let us introduce the core R functions in the dplyr package:

- *filter()*: extracts rows (observations) by logical vectors.
- *select()*: extracts columns (variables) by column names.
- *group_by()*: assigns rows into groups by column names.
- *mutate()*: creates new variables in a data frame.
- *summarise()*: collapses a data frame into summary statistics.
- *arrange()*: sorts row ordering based on column names.

These function names are self-descriptive: filter() makes a subset of the data set by extracting rows that meet specified conditions; select() extracts selected variables; group_by() creates a grouped data frame, which enables subsequent computations in mutate() and summarise() to be performed within each group; mutate() creates new variables through direct arithmetic operations of existing variables, canned functions, and user-defined functions; summarise() transforms a data set into statistics through canned functions or user-defined functions; and arrange() sorts the row order of the data set. These functions can be combined in any order to accomplish a desired data transformation. For example, one can extract a subset of the data by filter(), set groups by group_by(), compute summary statistics by summarise(), and use arrange() to sort the results.

Table 1 provides a comparison of these functions with the corresponding commands in Stata. Most applied economists would be very familiar with these data transformations, which is a helpful set of tools for getting started with *dplyr*. Here, we offer three reasons for why these *dplyr* functions can be perceived as more powerful than the corresponding functions in other programs such as Stata.

First, the *dplyr* functions are designed to be sequentially combined via *a pipe operator* (*%>%*), which makes the sequencing very smooth and natural to code. Each of the functions above takes a data frame object in the first argument and returns a data frame object, and this allows for piping, that is, applying functions sequentially by passing the output of one function into the first argument of the next. For

Table 1. Comparable Data Transformation Commands between R and Stata

Comparable Commands	
dplyr	STATA
filter(exp1, exp2, ..)	[if] [in] exp / keep if exp
select(varname1, varname2, ..)	keep varlist
arrange(varname1, varname2, ..)	sort varlist
mutate(newvar1 = exp1, newvar2 = exp2, ..)	generate/egen newvar = exp
summarise(newvar1 = exp1, newvar2 = exp2, ..)	collapse [(stat) varlist]
group_by(varname1, varname2,..)	egen .., group(varlist) / collapse .., by(varlist)

example, *func3(func2(func1(data,...), ...), ...)* can be rewritten as *data %>% func1(...) %>% func2(...) %>% func3(...)*. Piping makes R code more readable and breaks down a complex data manipulation into a sequence of simple steps. Notably, we can read a sequence of operations in plain English by substituting the *%>%* symbol with *then*. For example, start with the data, then apply *func1(...)*, then *func2(...)*, and then *func3(..)*. This makes data exploration approachable (the user has an intuitive framework for coding the first few functions), expandable (functions are easy to add on), and even rewarding (the resulting code can accomplish complex data transformations).

Second, the simplicity in needing to remember just six functions is empowering for the user. These functions condense the essence of data transformations needed for exploring data. Remembering these functions and piping them allows us to perform a myriad of data transformations without dedicating much brain power to formulating the coding instructions.

Third, R's data management environment is conducive to performing a series of data transformation and visualization tasks without any commitment to altering the working copy of the data set. R separately handles the task of transforming data from the task of saving the transformed data under a given name. Piping allows us to execute a series of data tasks without needing to overwrite the working data set. When it is desirable to save transformed data (e.g., creating different data summaries or using them in subsequent calculations), it is straightforward to keep multiple data sets in the working environment (i.e., just give new names to outputs).

With those six commands presented above, we can approach data exploration through iterative trials of data transformations and visualizations through extracting subsets, grouping, sorting, generating variables, and computing data summaries. Each iteration, sparked by an inquisitive hypothesis, offers the potential to reveal new aspects of the data. The interesting data patterns, correlations, anomalies, and outliers revealed in one inquiry can lead to another line of inquiry. By allowing improvisations through EDA, we create a sense of interaction with the data. After repeated use, these tools in R can give one an increased sense of confidence and control to explore the data at hand.

4.1 Farm Data

We now move to our demonstrations with real data. In the rest of the section, we examine the U.S. Census of Agriculture (2017).[10] for which various summary data are publicly available at the country, state, and

[10] Available at https://www.nass.usda.gov/Publications/AgCensus/2017/index.php and also in the supplementary appendix.

county levels. For convenience, the downloaded data set is separated into a national-level data set *us17*, state-level data set *state17*, and county-level data set *county17*. For *us17*, specifying some variables by *select()* and printing the first five rows yields:

```
us17 %>% select(census_table, Sector, Commodity, Item, geog_level, Value) %>% print(n=5)
## # A tibble: 82,025 x 6
##   census_table Sector  Commodity   Item                    geog_level  Value
##          <dbl> <chr>   <chr>       <chr>                   <chr>       <dbl>
## 1            1 ECONOM… FARM OPERA… FARM OPERATIONS - NUM… NATIONAL   2.04e6
## 2            1 ECONOM… FARM OPERA… FARM OPERATIONS - ACR… NATIONAL   9.00e8
## 3            1 ECONOM… FARM OPERA… FARM OPERATIONS - ARE… NATIONAL   4.41e2
## 4            1 ECONOM… AG LAND     AG LAND, INCL BUILDIN… NATIONAL   1.31e6
## 5            1 ECONOM… AG LAND     AG LAND, INCL BUILDIN… NATIONAL   2.98e3
## # … with 8.202e+04 more rows
```

Note that the national level data set alone contains over 80,000 rows. The state or county level data set will contain far more rows of data. To identify a variable of interest in a large data set like this, it is essential to have some understanding of its data structure. Two useful approaches here are to (1) become familiar with Quick Stats 2.0,[11] with which these data sets are consistently organized and (2) scan through published census of agriculture tables for its contents and organization.

Suppose that we are interested in the prevalence of small (those farms with less than \$100,000 of sales) and nonsmall farms (for the sake of discussion, say, farms with greater than \$100,000). The information needed for this is found in Table 2 of the U.S. and state census tables. We can extract the relevant information by specifying the table number in *filter()* and inspecting unique entries in the *Item* column:

```
# find the relevant Item
us17 %>% filter(census_table == 2) %>%
  select(Item) %>% unique()
## # A tibble: 144 x 1
##    Item
##    <chr>
##  1 COMMODITY TOTALS - OPERATIONS WITH SALES
##  2 COMMODITY TOTALS - SALES, MEASURED IN PCT OF FARM OPERATIONS
##  3 COMMODITY TOTALS - SALES, MEASURED IN $
##  4 COMMODITY TOTALS - SALES, MEASURED IN PCT OF FARM SALES
##  5 COMMODITY TOTALS - SALES, MEASURED IN $ / OPERATION
##  6 CROP TOTALS - OPERATIONS WITH SALES
##  7 CROP TOTALS - SALES, MEASURED IN PCT OF FARM OPERATIONS
##  8 CROP TOTALS - SALES, MEASURED IN $
##  9 CROP TOTALS - SALES, MEASURED IN PCT OF FARM SALES
## 10 GRAIN - OPERATIONS WITH SALES
## # … with 134 more rows
```

The information we need is a cross tabulation between the *Item* being "COMMODITY TOTALS—OPERATIONS WITH SALES" and the *Class*, two variables that contain the number of farms and the information about farm sales class. We use *filter()* to pinpoint the data we are seeking.

[11] Accessible at https://quickstats.nass.usda.gov/.

```
# find the relevant Item and Class
farm_class_US <- us17 %>%
    filter(
      census_table == 2,
      grepl("COMMODITY TOTALS - OPERATIONS WITH SALES", Item),
      !is.na(Class)
    ) %>% select(Class, Value)

farm_class_US
## # A tibble: 16 x 2
##    Class                                    Value
##    <chr>                                    <dbl>
##  1 FARM SALES: (LESS THAN 1,000 $)         603752
##  2 FARM SALES: (1,000 TO 2,499 $)          187949
##  3 FARM SALES: (2,500 TO 4,999 $)          185341
##  4 FARM SALES: (5,000 TO 9,999 $)          208074
##  5 FARM SALES: (10,000 TO 19,999 $)        174780
##  6 FARM SALES: (20,000 TO 24,999 $)         53438
##  7 FARM SALES: (25,000 TO 39,999 $)        100490
##  8 FARM SALES: (40,000 TO 49,999 $)         43623
##  9 FARM SALES: (50,000 TO 99,999 $)        119434
## 10 FARM SALES: (100,000 TO 249,999 $)      130932
## 11 FARM SALES: (250,000 TO 499,999 $)       87839
## 12 FARM SALES: (500,000 TO 999,999 $)       69703
## 13 FARM SALES: (1,000,000 OR MORE $)        76865
## 14 FARM SALES: (1,000,000 TO 2,499,999 $)  53611
## 15 FARM SALES: (2,500,000 TO 4,999,999 $)  14366
## 16 FARM SALES: (5,000,000 OR MORE $)        8888
```

Note that the national data set provides the aggregate record for the sales class of $5,000,000 or more as the most detailed information on larger farms. If similar operations are applied to the state or county level data, one would find that all sales classes above $1,000,000 and above $500,000 are aggregated, respectively.

Let's turn to county-level data. By continuing on the previous example, suppose that we want to count farms by a binary sales-class consisting of small farms (label *S*) versus not-small farms (label *NS*) at the county level. We do this by selecting relevant data, creating a new class variable (by comparing the sales class in the data to user-defined reference *class_S* that contains a vector of class names for those under $100,000 in sales), and summarizing the number of farms by county and the binary sales-class:

```
farms <- county17 %>%
  filter(
    census_table == 2,
    grepl("COMMODITY TOTALS - OPERATIONS WITH SALES", Item),
    !is.na(Class), Co_name != "NULL"
    ) %>%

  # create a new variable indicating sales < $100k
  mutate(class_S_NS = ifelse(Class %in% class_S, "S", "NS")) %>%
  group_by(St_code, St_name, Co_code, Co_name, class_S_NS) %>%
  summarise(Value = sum(Value, na.rm = T))

# show the top 10 county for the numbers of small farms
farms %>% filter(class_S_NS=="S") %>% arrange(desc(Value)) %>% head(n = 10)
## # A tibble: 10 x 6
## # Groups:   St_code, St_name, Co_code, Co_name [10]
##    St_code St_name Co_code Co_name   class_S_NS Value
##    <chr>   <chr>   <chr>   <chr>     <chr>      <dbl>
##  1 04      AZ      001     APACHE    S           5529
##  2 06      CA      073     SAN DIEGO S           4571
##  3 48      TX      367     PARKER    S           4521
##  4 04      AZ      017     NAVAJO    S           4181
##  5 48      TX      231     HUNT      S           4040
##  6 41      OR      005     CLACKAMAS S           4013
##  7 15      HI      001     HAWAII    S           3929
##  8 12      FL      083     MARION    S           3776
##  9 48      TX      497     WISE      S           3610
## 10 08      CO      123     WELD      S           3407

# show the top 10 county for the numbers of non-small farms
farms %>% filter(class_S_NS == "NS") %>% arrange(desc(Value)) %>% head(n = 10)
## # A tibble: 10 x 6
## # Groups:   St_code, St_name, Co_code, Co_name [10]
##    St_code St_name Co_code Co_name     class_S_NS Value
##    <chr>   <chr>   <chr>   <chr>       <chr>      <dbl>
##  1 42      PA      071     LANCASTER   NS          2382
##  2 06      CA      019     FRESNO      NS          2240
##  3 06      CA      107     TULARE      NS          1800
##  4 06      CA      077     SAN JOAQUIN NS          1414
##  5 06      CA      099     STANISLAUS  NS          1305
##  6 06      CA      047     MERCED      NS          1100
##  7 27      MN      145     STEARNS     NS          1091
##  8 19      IA      167     SIOUX       NS          1070
##  9 06      CA      097     SONOMA      NS           849
## 10 55      WI      043     GRANT       NS           828
```

When we compare where small (S) and nonsmall farms (NS) are numerous, the two lists of top counties are not geographically overlapping for these two farm classes. Summing up the number of farms within each binary sales class yields:

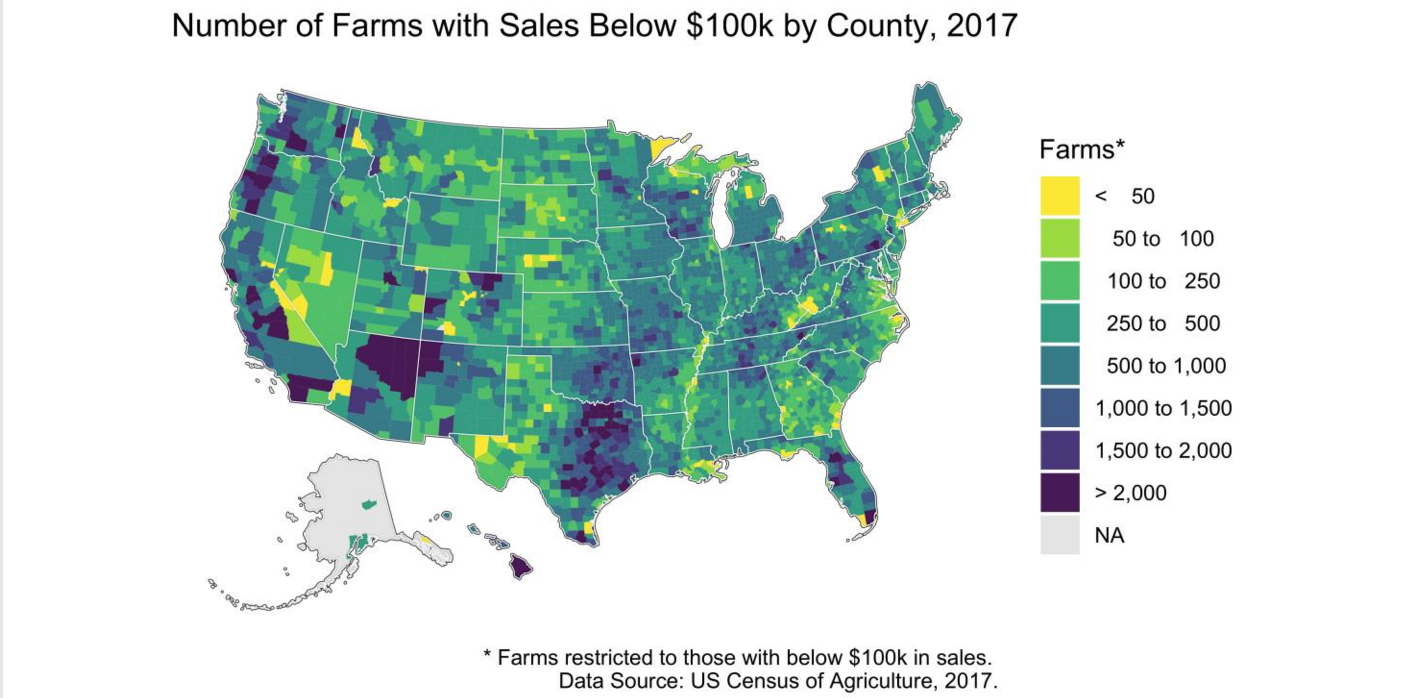
```
# total number of farms by class
farms %>% group_by(class_S_NS) %>%
  summarise(subtotal = sum(Value, na.rm = T)) %>%
  ungroup() %>%
  mutate(total = sum(subtotal, na.rm = T),
         fraction = round(subtotal / total, 2))
## # A tibble: 2 x 4
##   class_S_NS subtotal   total fraction
##   <chr>         <dbl>   <dbl>    <dbl>
## 1 NS           365339 2042220     0.18
## 2 S           1676881 2042220     0.82
```

Of the 2 million farms for which the census gathered data, roughly 1.68 million farms (82 percent) had less than $100,000 in revenues. The USDA defines a farm to be "any place from which $1,000 or more of agricultural products were produced and sold, or normally would have been sold, during the census year" (O'Donoghue et al. 2009). In fact, over 600,000 farms do not have sales above $1,000 in 2017, as shown in the first summary *farm_class_US* above. Although the definition of farms in USDA statistics has been debated previously, no change has been made (O'Donoghue et al. 2009).

One strength of R for agricultural data analysis is to be able to produce geographical representations of data. With county-level data paired with the state-county Federal Information Processing Standards (FIPS) codes, it is straightforward to project the data on maps. For instance, the following sample code shows how variable *var1* in data set *data* can be mapped at the county level:

```
# merge county level data with geographic data and generate a color-coded map
left_join(geo_county, data,  by = c("GEOID" = "FIPS")) %>%
    ggplot() +
    geom_sf(aes(fill = var1)) +
    coord_sf(datum = NA) + theme_minimal()
```

Here, *geo_county* contains the geometry data of U.S. county boundaries (which can be replicated by downloading any county-level information of the American Community Survey with *tidycensus* package). Layer *geom_sf()* handles the geometry aesthetic and here supplies a layer that fills county shapes with different colors depending on the value of *var1*. Additional layers *coord_sf(datum = NA)* and *theme_minimal()* instruct how to remove data plot graphics like axes and data plot area, giving a clean finish to the map output. Figures 7 and 8 provide examples of mapping the farm distributions using the binary revenue-class variable defined above.



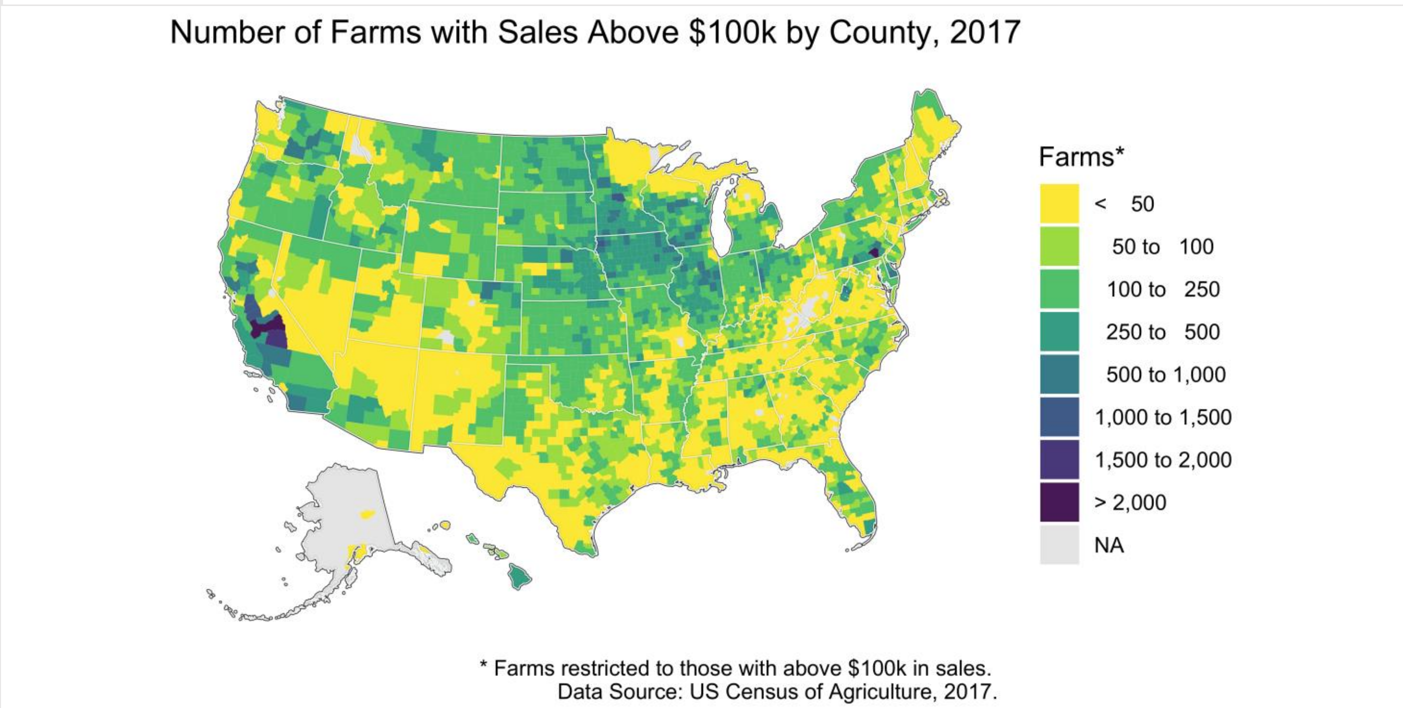


Figure 7. Map of Farm Counts Using the Binary Sales-Revenue Class in the 2017 U.S. Census of Agriculture

The first map shows the distribution of farms with sales less than $100,000, and the second map shows the distribution of farms with sales above $100,000.

In addition to the raw farm counts, the next map considers the relative prevalence of the small and nonsmall farms (Figure 8). This approach may more clearly highlight the geographic concentrations of farms in different farm-size classes across counties, especially in terms of how the concept of a farm (i.e., the revenue size of active farming and what meets the criteria for being considered a farm in the U.S. Census of Agriculture database) systematically varies across geography.

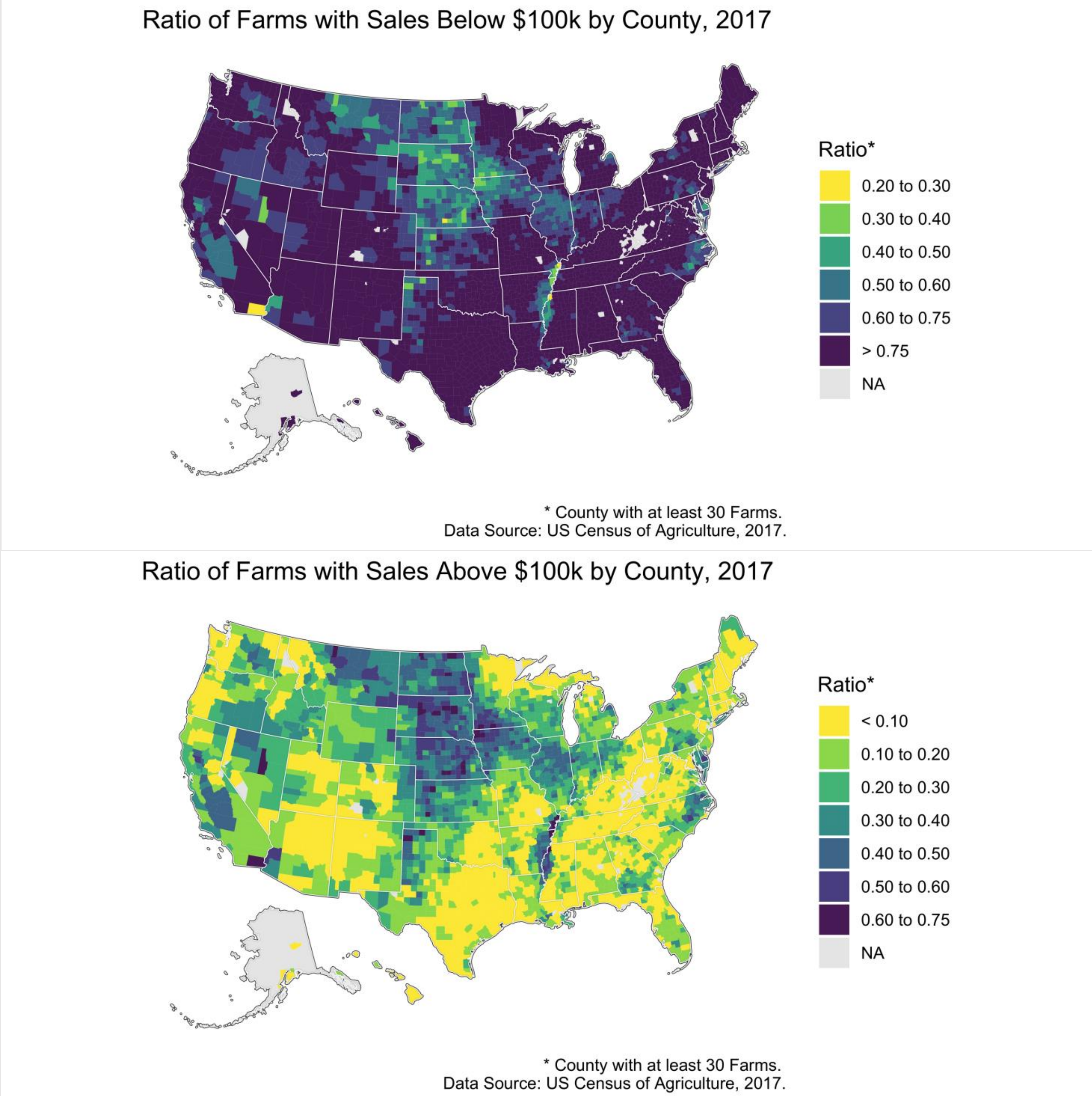


Figure 8. Map of Relative Farm Counts Using the Binary Sales-Revenue Classes in the 2017 U.S. Census of Agriculture

The two maps show the relative frequency of farms with sales below $100,000 (first), and the farms with sales above $100,000 (second).

Next we turn to differences across major farming industries. Suppose that we want to see how the concept of a farm differs across industries. We can examine the distributions of farm numbers and sales values this time by industry. In the first example, we show Sankey flow charts (we used the *flipPlots* package; Figures 9 and 10), which illustrate the contributions of different segments of data to the grand total like various streams combining into a river. Here, we add an intermediate layer that represents the subtotals by farm-sales class. For this purpose, we consider four levels of sales classes; marginal (less than

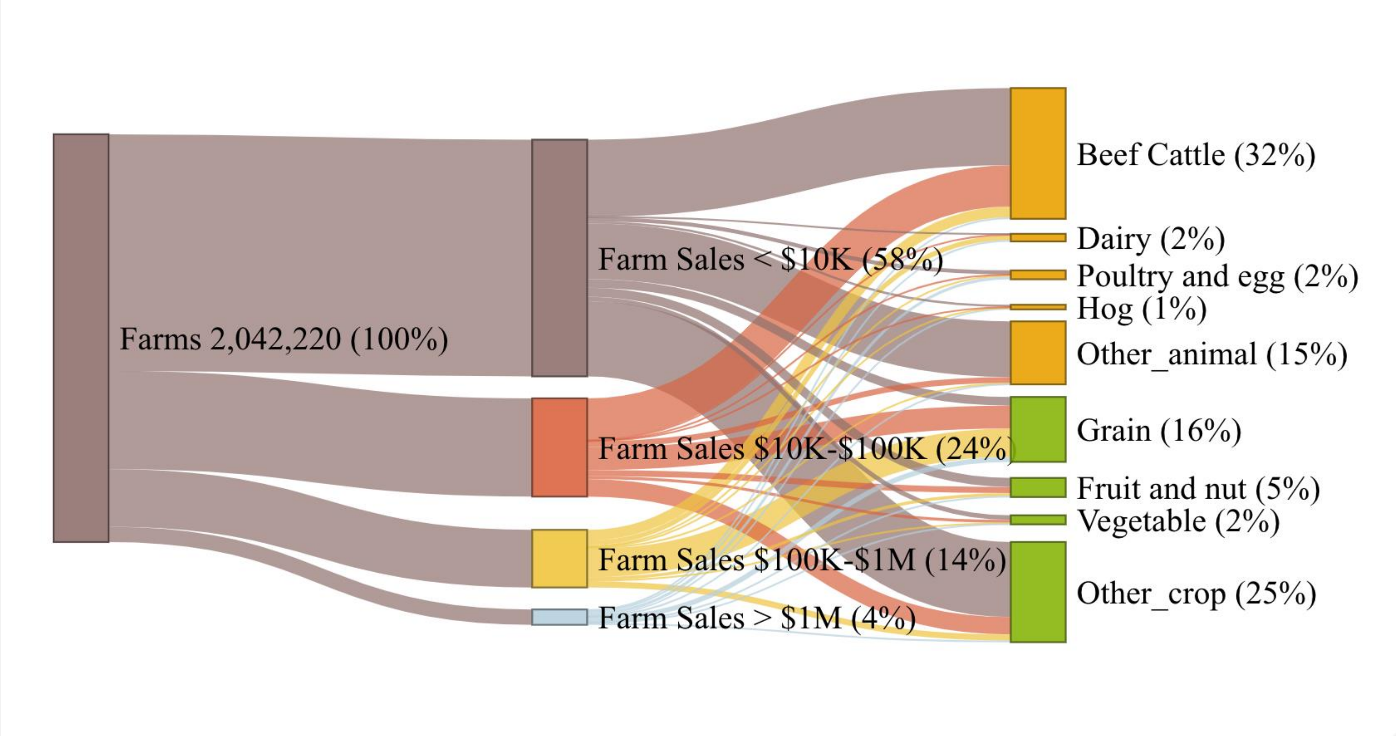


Figure 9. Sanky Flow Chart of Farm Counts by Sales and Industry from the 2017 U.S. Agricultural Census Data

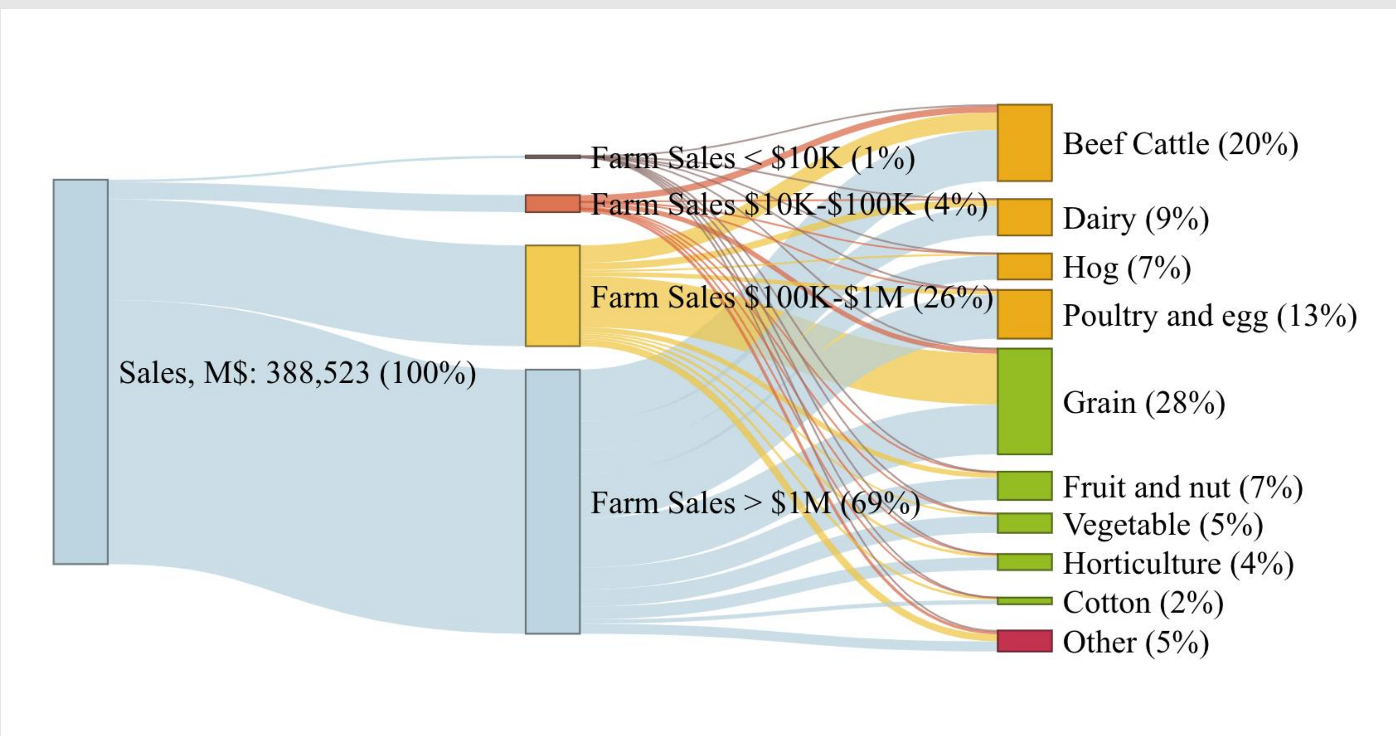


Figure 10. Sanky Flow Chart of Sales Values by Farm Sale Class and Industry from the 2017 U.S. Agricultural Census Data

$10,000), small ($10,000 to $100,000), medium ($100,000 to $1,000,000), and large (greater than $1,000,000). These charts show relationships among the farm numbers and sales values through the lens of farm size and by the industry.

Figure 9 shows that nearly 60 percent of the farms in the census are marginal producers with less than $10,000 in sales. Anyone who uses statistical information in the agricultural census must be aware of how the presence of these marginal farms impacts statistics like the averages per farm. On the other hand, the large farms with over $1,000,000 in sales revenues accounted for roughly 4 percent of the farm population, but produced nearly 70 percent ($268,000,000,000) of agricultural products in sales values (Figure 9 and 10). About 88 percent of the farms are classified as producers of grain, beef cattle, "other crop," or "other animal" products (suggesting that only a small fraction of farms produce poultry and eggs, hogs, dairy, fruit and nuts, and vegetables). The majority of the medium-sized farms are grain producers. Grain production is unique in that its sales are not dominated by large-sized farms, as its total sales contribution is roughly equally split between medium- and large-sized farms.

4.2 How Does Farming Differ across States and Industries?

We next explore the characteristics of farm economies using industry statistics across states. It is common to see a ranking of states by sale values for a given industry. Here, we consider a slightly different comparison in which we visualize the relative size of a state's crop and livestock sectors. By selecting certain variables from the state-level census data, we constructed the data set *df_NAICS* as organized by state and North American Industry Classification System (NAICS) code. In the following code example, we aggregate the sales revenue by state and NAICS category (i.e., crop or livestock), converting the data set into the "wide" format by distributing the sales value into "crop" and "livestock" variables, and then plot the data with the annotation of state names if the state exceeds certain sales value thresholds (Figure 11):

```
# see "ag_examples.R" for creating data set "df_NAICS"
load(file="data sets/df_NAICS.RData")

crop_vs_animal <-
  df_NAICS %>% filter(!is.na(NAICS_cat)) %>%
  group_by(St_code, St_name, USDA_region, NAICS_cat) %>%
  summarise(revenue_sales = sum(revenue_sales, na.rm = T) / 10^9) %>%
  pivot_wider(names_from = NAICS_cat, values_from = revenue_sales)

crop_vs_animal %>%
  ggplot(aes(x = Crop, y = Livestock, color = USDA_region, shape = USDA_region)) +
  geom_point() +
  geom_label_repel(aes(label = St_name), show.legend = FALSE,
            data = crop_vs_animal %>% filter(Crop > 6 | Livestock > 7)) +
  labs(x = "Crop Agriculture Revenue, $ billion",
      y = "Livestock Agriculture Revenue, $ billion",
      caption = "Data Source: US Census of Agriculture, 2017.")
```

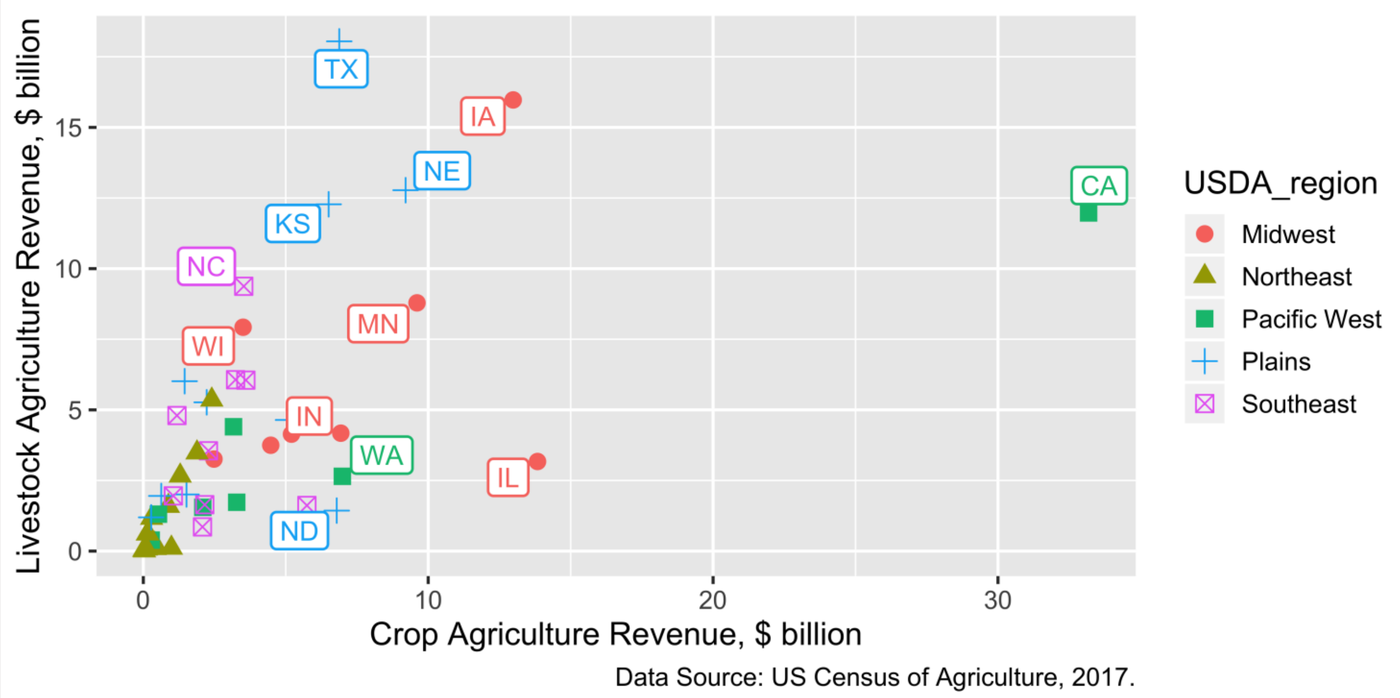


Figure 11. Livestock versus Crop Output by State (Selectively Labeled) from the 2017 U.S. Agricultural Census Data

It is clear that California is an exceptionally large agricultural state in both crop and livestock production. Also, one can see that Illinois, Washington, and North Dakota are specialized in crop production; Texas, Kansas, North Carolina, and Wisconsin are specialized in livestock production; and Iowa, Nebraska, and Minnesota are relatively balanced between the revenues from crop and animal agriculture (Figure 11).

In gathering various USDA National Agricultural Statistics Service (NASS) and census data, it is convenient to directly download them using an API (e.g., using the *rnassqs* package). The following is an example for obtaining the aggregate land asset value and net farm income for the poultry industry from the agricultural census data:

```
library(rnassqs)
NASSQS_TOKEN <- "C9B668A9-3062-..." # use your token
nassqs_auth(key = NASSQS_TOKEN)

# check asset and profitability of poultry sector
asset_profit_poultry <- nassqs(list(
  source_desc = "census",
  agg_level_desc = "national",
  domaincat_desc= "NAICS CLASSIFICATION: (1123)",
  short_desc = c("AG LAND, INCL BUILDINGS - ASSET VALUE, MEASURED IN $",
              "INCOME, NET CASH FARM, OF OPERATIONS - NET INCOME, MEASURED IN $"),
  year = c(2012, 2017))) %>%
  select(sector_desc, short_desc, state_alpha, year, commodity_desc, Value)

# note: only 2012 and 2017 data are available
```

Next, suppose that we ask, “what does it take for a farm to thrive?” To explore this question, it is instructive to compare the average utilization of capital and labor per operator across states and agricultural industries. Here we define capital as the sum of the total asset value of land, buildings, and machinery for crop farming. For livestock farms, we add the value of livestock inventory for poultry (broiler chickens, nonbroiler chickens, and turkeys), hogs, dairy cows, and beef cattle using NASS survey and census statistics. For the poultry industry, we further add an estimated value of facility (for processing, hatchery, and feed mills that are largely owned by integrators) at the estimated rate of $3.5 per chicken-equivalent production (using the approximate rate based on the reporting by Wood 2018). Note that these asset values are only a crude approximation (Figures 12 and 13).

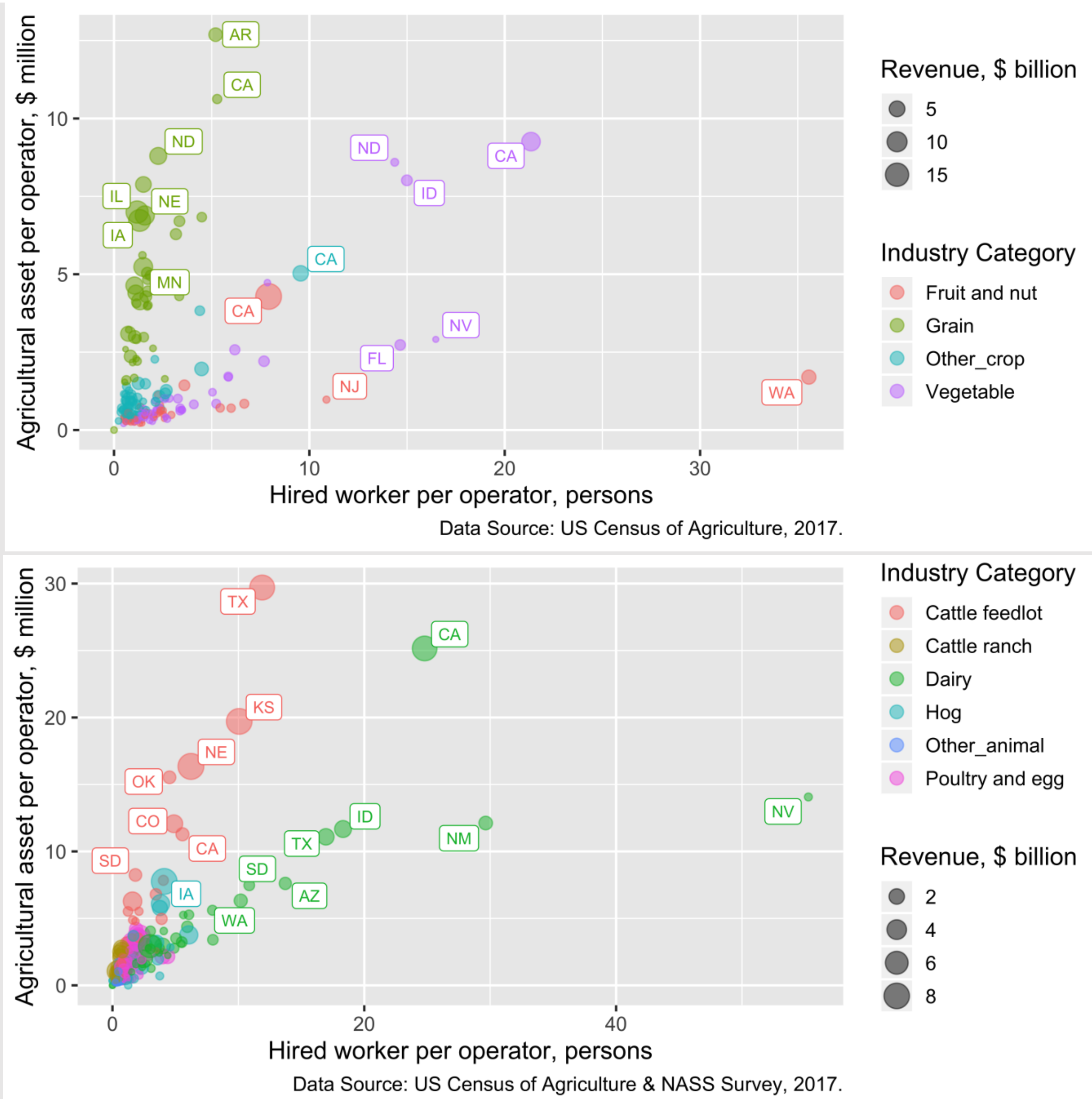


Figure 12. Capital and Labor per Operator by State and Agricultural Industry from the 2017 U.S. Agricultural Census and NASS Survey

Note: The top plot shows the data plot for crop industries, and the bottom plot shows that for livestock industries.

Grain production is more capital intensive than other types of crop farming, whereas fruit and nut production tends to be more labor intensive (Figure 12). In most states, grain producers are likely to require from $2,000,000 to 5,000,000 of capital asset, for which much of the value can be attributed to the value of the land. The data points for the "other crop" category are clustered together near zero except California, potentially because this category contains many marginal producers with less than $10,000 in sales.

For livestock agriculture, it is clear that cattle feedlot production is capital intensive, in which much of the capital is tied to the value of cattle inventory. In contrast, the data points for cattle ranch operations are clustered near zero. Indeed, beef producers are very different between ranch and feedlot operations since a typical feedlot manages much larger herds of cattle than a typical ranch. Dairy production is both capital and labor intensive; the average dairy operator in California, Nevada, New Mexico, Idaho, and Texas employs over $10,000,000 of assets and near 20 hired workers or more. In poultry and egg production, the notion of a farm operator itself is rather different because many producers operate under contracts with larger integrators such as Tyson, Pilgrim's Pride, and Perdue. According to Alonzo (2016), in 2015, the top five integrators had over 60 percent of market share in the poultry and egg industry.

In the plot above, we see that the data points for some types of operations like grain, dairy, and cattle feedlot production, visually line up with underlying linear trends. We can obtain an ordinary least squares (OLS) estimate of this trend using the *lm()* function for linear models.

```
# OLS estimation by lm(.) function

# Regress asset dollars on hired labor for dairy data
lm( formula = asset_per_unpaid ~ hired_to_unpaid,
    data  = df_NAICS_simple %>%
      filter(revenue_sales > .01,
             NAICS_simple == "Dairy")
  ) %>% summary()
##
## Call:
## lm(formula = asset_per_unpaid ~ hired_to_unpaid, data = df_NAICS_simple %>%
##     filter(revenue_sales > 0.01, NAICS_simple == "Dairy"))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.3776 -0.9915 -0.4703  0.4672 14.1909
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.62684    0.48002   3.389  0.00147 **
## hired_to_unpaid  0.37662    0.04181   9.009 1.23e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.695 on 45 degrees of freedom
## Multiple R-squared:  0.6433, Adjusted R-squared:  0.6354
## F-statistic: 81.16 on 1 and 45 DF,  p-value: 1.231e-11
```

lm() produces a linear model class object, on which applying the *summary()* function gives an informative output with a table of coefficients and common goodness-of-fit statistics. Here, we see that for each hired farm worker, the estimated slope coefficient implies that a typical dairy farm would employ $377,000 worth of capital asset per hired farm worker. Let's add a few more variables to this regression, such as regional fixed effects and a debt-to-income ratio:

```
# Add more variables: region dummies, debt-to-income ratio
lm( formula = asset_per_unpaid ~
      hired_to_unpaid + USDA_region + I(debt_at_5pct/revenue_sales),
    data  = df_NAICS_simple %>%
      filter(revenue_sales > .01,
             NAICS_simple == "Dairy")
  ) %>% summary()
##
## Call:
## lm(formula = asset_per_unpaid ~ hired_to_unpaid + USDA_region +
##     I(debt_at_5pct/revenue_sales), data = df_NAICS_simple %>%
##     filter(revenue_sales > 0.01, NAICS_simple == "Dairy"))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.7925 -0.8585  0.0090  0.5823 12.8283
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    0.22568    1.91030   0.118   0.9065
## hired_to_unpaid                0.30129    0.05387   5.593 1.76e-06 ***
## USDA_regionNortheast           0.04172    1.22488   0.034   0.9730
## USDA_regionPacific West        3.59442    1.66197   2.163   0.0366 *
## USDA_regionPlains              1.48626    1.30884   1.136   0.2629
## USDA_regionSoutheast          -0.09535    1.40162  -0.068   0.9461
## I(debt_at_5pct/revenue_sales)  2.12396    2.50791   0.847   0.4021
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.617 on 40 degrees of freedom
## Multiple R-squared:  0.701,  Adjusted R-squared:  0.6562
## F-statistic: 15.63 on 6 and 40 DF,  p-value: 3.852e-09
```

lm() treats character-string variables as factor/categorical variables and inserts indicator dummies for each group. Also, to create a new variable from manipulating existing variables, one can use the *I(.)* operator in the linear model formula. The estimates show that after accounting for regional differences in the intercept and the relative use of debt to sales revenues, the average dairy farm capital asset is about $301,000 per hired worker.

Last, we briefly turn to the capital structure and return on asset in farming (Figure 13). Keep in mind that agricultural commodity prices vary from year to year, which causes the profitability to fluctuate. Some states had a particularly profitable year in vegetable, fruit, and nut production in 2017. The poultry and egg industry also had a particularly profitable year (note: the industry's net income doubled from 2012 to 2017, according to the Census of Agriculture). Dairy producers in states with large-sized dairy operations attained relatively high returns, while they were also highly leveraged (Figure 13).

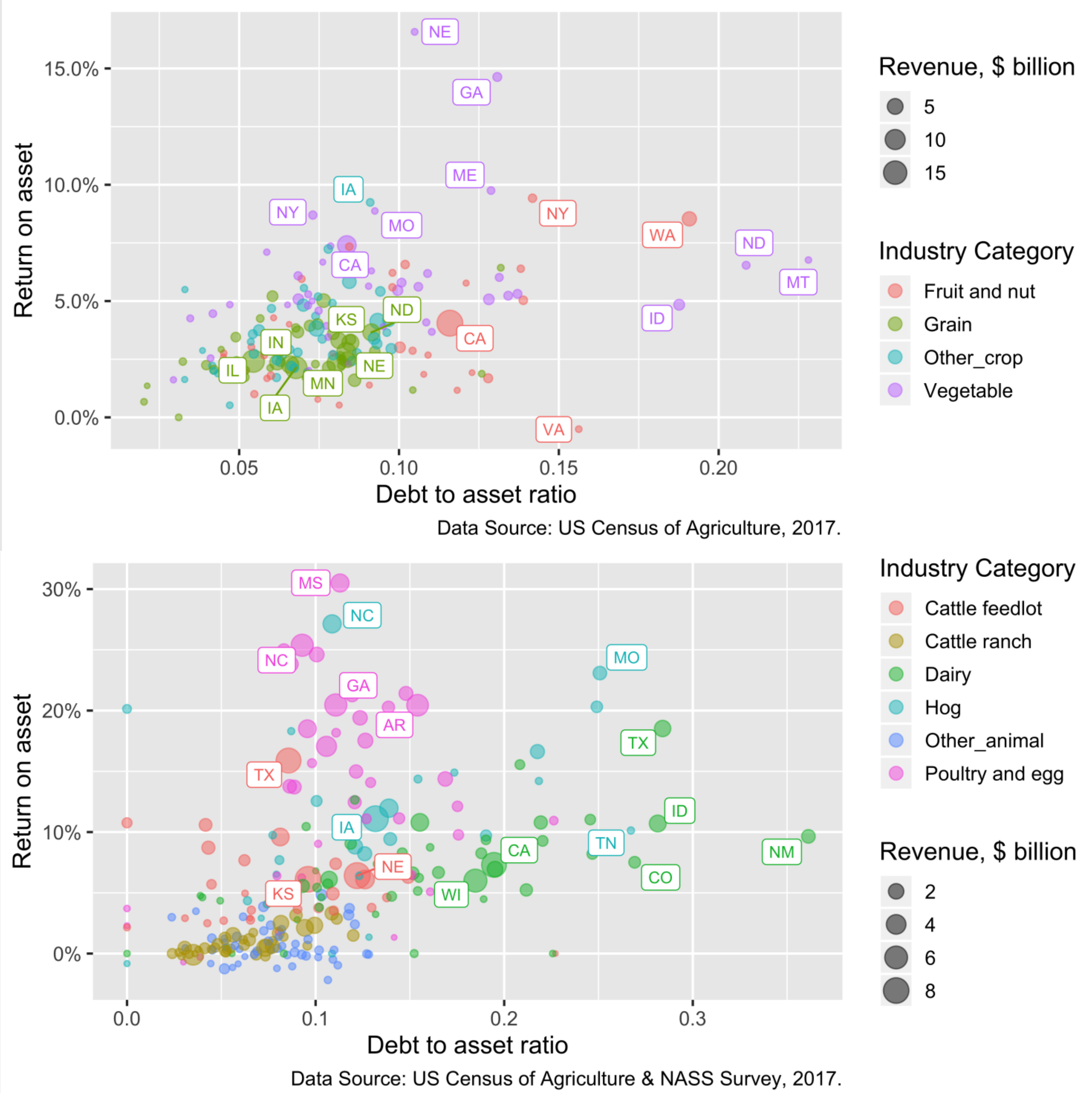


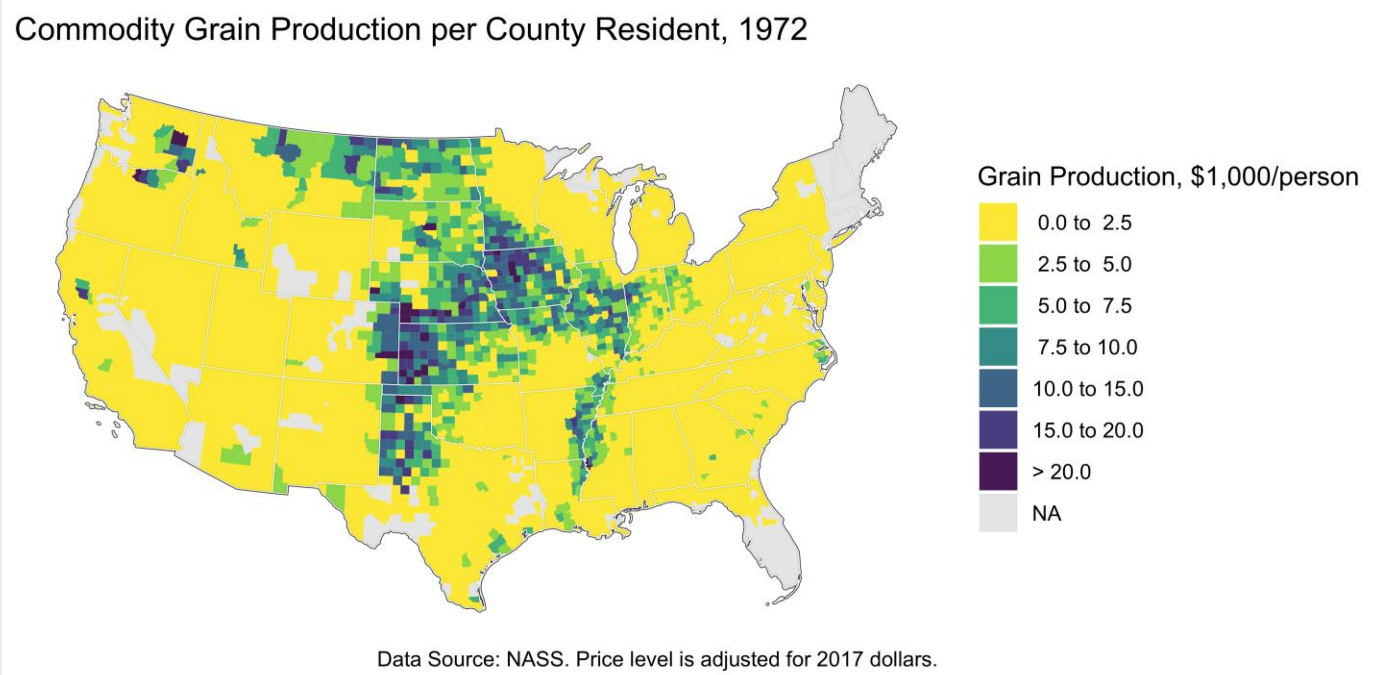
Figure 13. Return and Debt per Asset by State and Agricultural Industry from the 2017 U.S. Agricultural Census and NASS Survey

Note: The first plot shows the data plot for crop industries, and the second plot shows data for livestock industries.

5 Analytical Demonstration

For further illustration, this section presents an example of analytical data exploration on the topic of rural population change. In particular, we investigate whether there are systematic relationships between the intensification of grain farming and rural depopulation during the period 1972–2017. In preparation of the data set, we selected the data for 1972 as the beginning of this time span because the NASS survey data in 1970 had a large number of missing data points. For the data beyond 1982, we assigned missing grain production values with zero if the county had a nonmissing value in the 1982 data. All grain production values were expressed in 2017 dollars.

We first generate two maps: one for the grain production by county in 1972 and the other for the change in grain production from 1972 to 2017 (Figure 14). The first map also shows that much of the Midwest had highly active grain production in 1972. The second map highlights a relative decline in grain production in many parts of the country, while the Midwest and a part of the South increased their grain production.



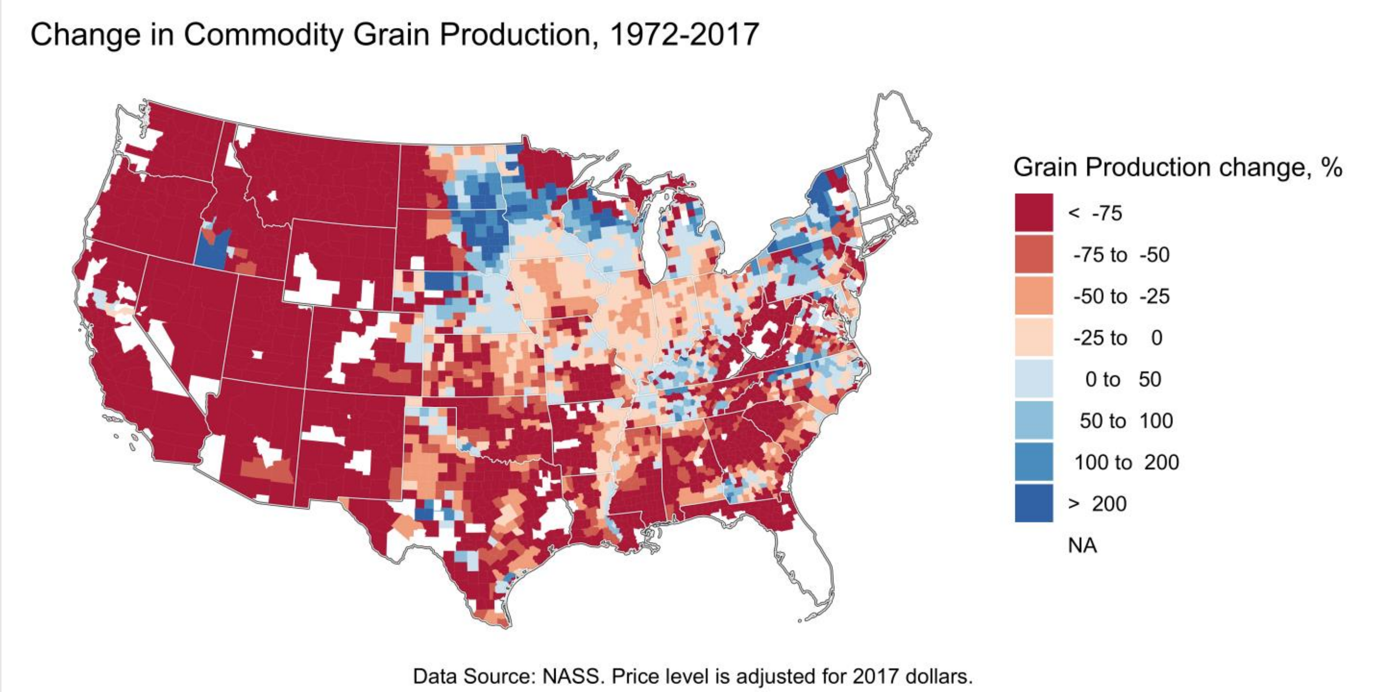


Figure 14. Map of Grain Production in 1972 and Production Change from 1972 to 2017

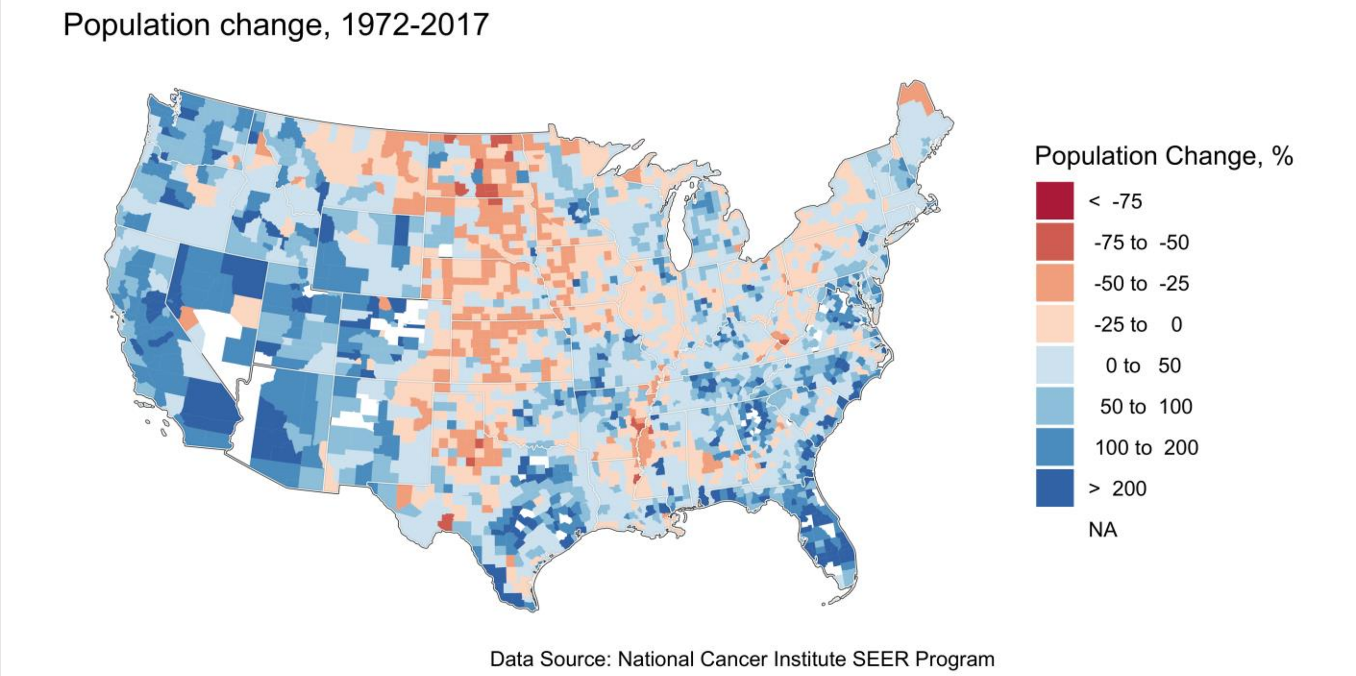


Figure 15. Map of Population Change, 1972–2017

We next map the overall population change during the same period (Figure 15). It is clear that the Midwest experienced the most significant population loss as a region. The two sets of maps together appear consistent with a narrative that increased mechanization of grain production required fewer and fewer laborers, which most severely affected the population in the Midwest (Johnson and Fuguitte 2000; Walzer 2003; White 2008; Longwoth 2009).

To further investigate the relationship between grain farming and population change, we plot county-level data against per capita grain production. In Figure 16, the top row contains a data plot of the raw data points (A) and a plot in the log-scale on the horizontal axis (B). The latter plot appears to suggest a negative correlation between the population change and the grain production per person in 1972. This correlation may be spurious because grain production per person may be affected by declining county population trends. Thus, we substitute this measure with the total grain production in the county (C) as well as the percentage change in grain production for 1972–2017 (D). For the latter, the cluster of data points at -100 percent change represents the counties that produced some grain in 1972 and had no sales records in 2017. These data plots seem to corroborate weak negative correlations between grain production and population change.

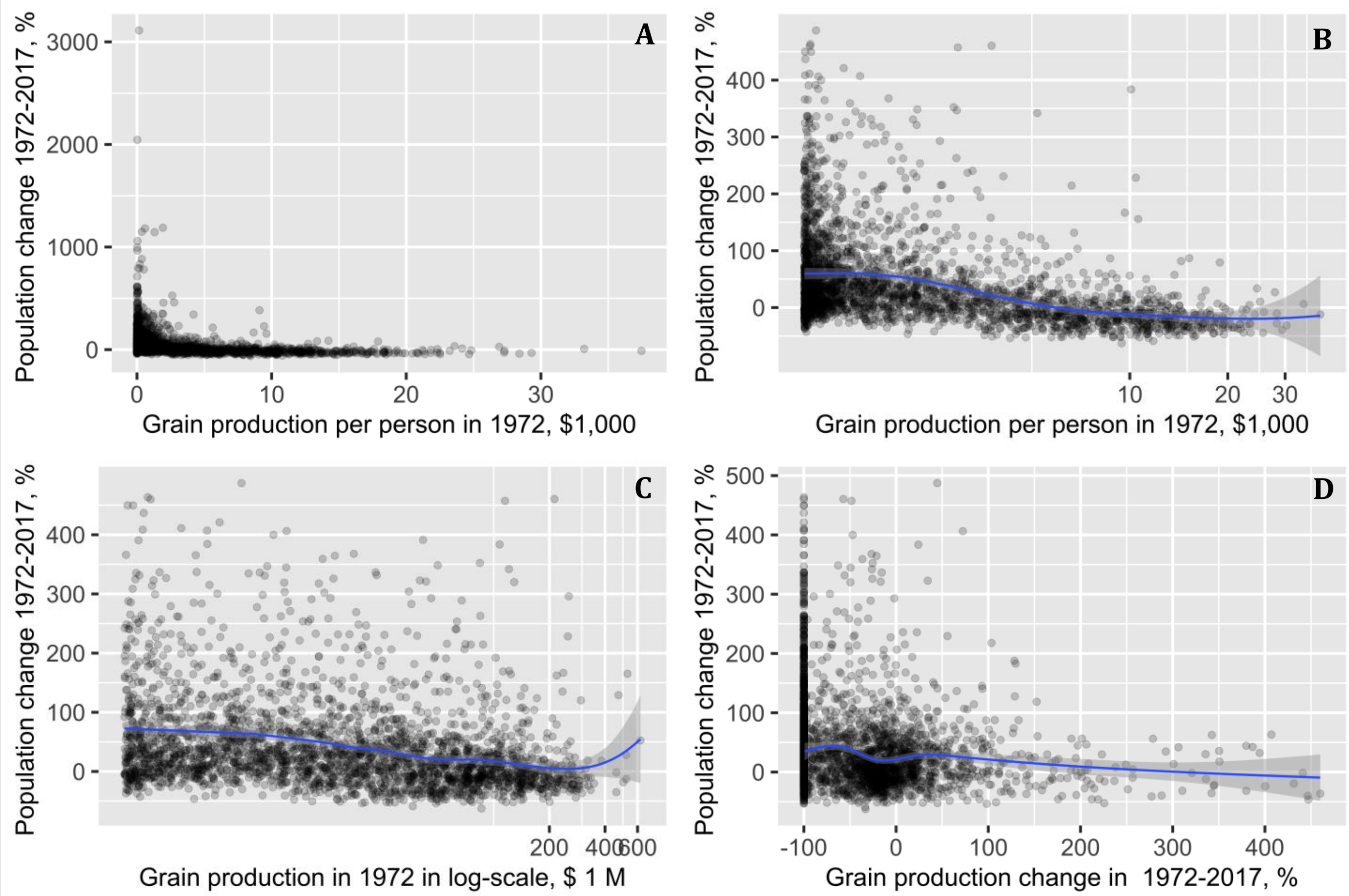


Figure 16. Scatter Data Plots of Grain Production and Population Change

Note: Top row figures use grain production per person in 1972 on the horizontal axis in the raw data scale (A) and the logarithmic scale (B). The bottom figures use grain production in log-scaled dollars (C) and grain production in percentage change (D).

Analytically, let us consider an ordinary least squares regression of the form

$$y_{is} = \alpha_s + \mathbf{x}_{is}\boldsymbol{\beta} + \varepsilon_{is}$$

where y_{is} is population change in county i in state s from 1972 to 2017, α_s are state fixed effects, $\mathbf{x}_{is}$ a vector of covariates, and ε_{is} an error term. For $\mathbf{x}_{is}$, we include grain production in 1972, the change in grain production from 1972 to 2017, and a dummy variable corresponding to the value of -100 percent changes. Given that some counties are much larger than others in terms of land area or in terms of population, we consider two models based on the county-level grain production per person (column (1)) along with total grain production (column (2)). We estimate the above equation using the linear regression model function *lm()* and summarize selected coefficients using the *stargazer* package.

```
lm_1 <- lm(pop_tot_ch_pct_72_17 ~ ln_grain_prod_person_1972 + grain_ch_pct_72_17 +
             (grain_ch_pct_72_17 == -100) + St_name,
           data = df_pop_grain)

lm_2 <- lm(pop_tot_ch_pct_72_17 ~   ln_grain_prod_1972 + grain_ch_pct_72_17 +
             (grain_ch_pct_72_17 == -100) + St_name,
            data = df_pop_grain)
```

Table 2. Estimate of Grain Production and Populations Change from 1972-2017

Variable	Population Change, % 1972–2017	
	Model 1	Model 2
Log of grain production per capita, 1972	-34.293***	
(ln_grain_prod_person_1972)	(2.101)	
Log of grain production, 1972		-7.140***
(ln_grain_prod_1972)		(1.282)
Change in grain production, 1972–2017	-0.096***	-0.090***
(grain_ch_pct_72_17)	(0.024)	(0.025)
Indicator for ceased grain production	-8.785**	-0.706
(grain_ch_pct_72_17==-100)	(4.049)	(4.684)
State fixed effects	Yes	Yes
Observations	2,727	2,727
Adjusted R squared	0.286	0.224
Residual Std. Error	65.347	68.124

Note: Statistical significance $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The two models differ in the grain production variable specified either as per capita within the county or the county total.

The results suggest negative associations between the grain production variables and population change, while controlling for unobservable fixed factors at the state level (Table 2). In terms of magnitudes, the first model indicates that a 10 percent higher grain production *per person* in 1972 is associated with an additional 3.4 percent reduction in the county population, while the second model suggests a 10 percent higher grain production in the county total is similarly associated with a 0.7 percent reduction. Of the models, the first model is more closely aligned with the relative importance of grain production in the county's economy and is here shown to be more strongly negatively correlated with the population change. The two models also suggest that a 10 percent *increase* in grain production from 1972 to 2017 is associated with an additional 0.9 to 1.0 percent decline in the population.

To examine the geographic distribution of the errors, we add the estimation errors to the data set by the *add_residual()* function from the *modelr* package:

```
# add model predictions, except states that have no grain production
df_pop_grain_res <- df_pop_grain %>%
  filter(!(St_name %in% c("CT", "DC", "MA", "ME", "NH", "RI", "VT"))) %>%
  add_residuals(lm_1, var = "resid_lm_1") %>%
  add_residuals(lm_2, var = "resid_lm_2")
```

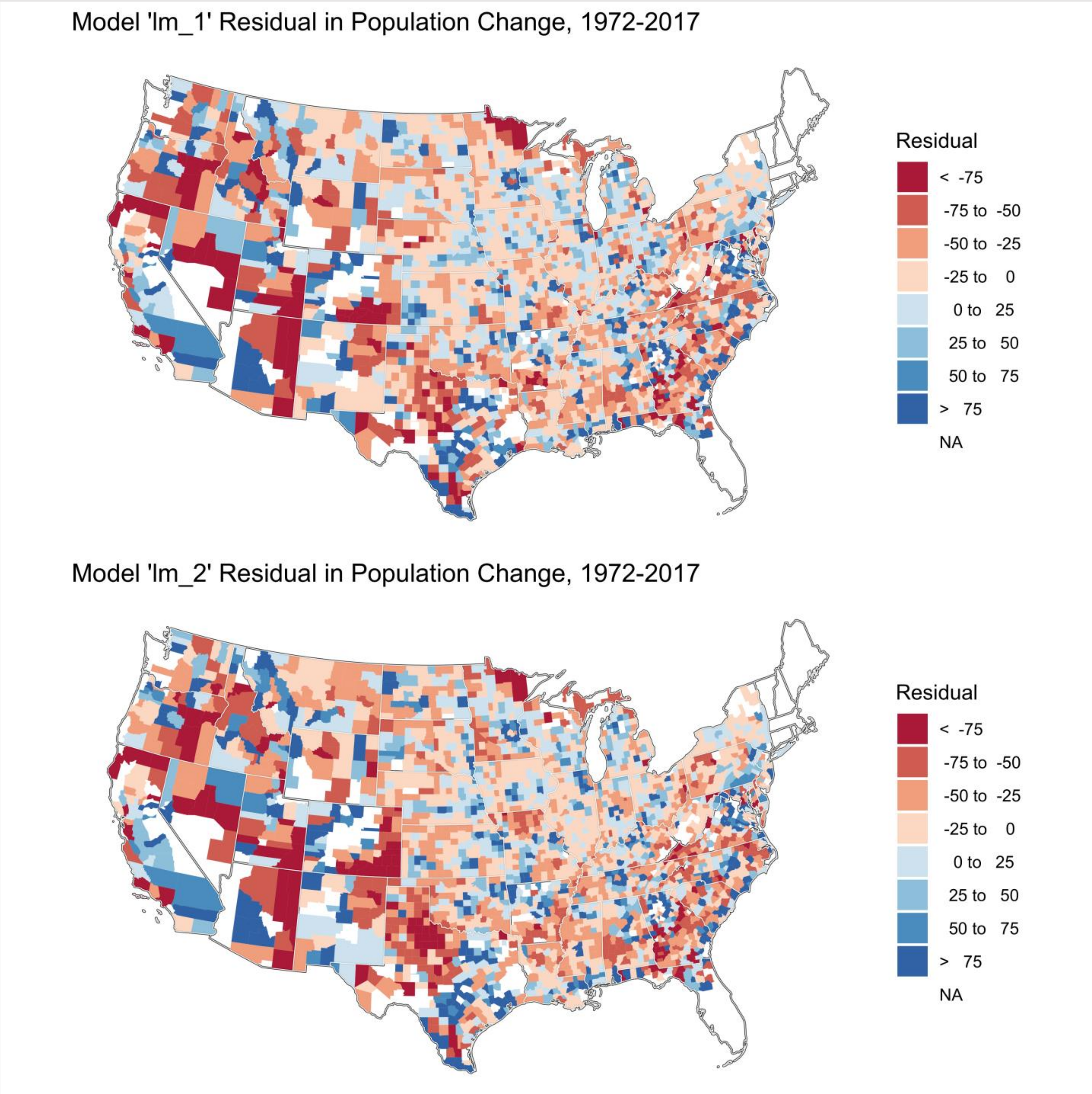


Figure 17. Maps of Model Residuals After Fitting Populating Change with Grain Production Data

These errors on the map (Figure 17) show that the residuals from the two models are qualitatively very similar. Given the fixed effects, the residuals are not concentrated in any particular state. The counties with dark red and dark blue shades are those that experienced particularly large population declines and gains respectively, net the state-level average trends.

In addition to the average effects shown above, we examine how such effects may vary across age groups. To explore this, we first map the population change for two age groups of 15–29 and 60 and older (Figure 18). The first map shows that there are fewer young adults in much of rural America today compared with 1972, particularly in the Great Plains. The second map shows an increase in the elderly population in many parts of the country from 1972 to 2017, except some segments of the Great Plains.

We examine different patterns of associations by applying the previous model to subsets of the data across age groups and time periods. For example, Table 3 presents the results for two age groups (15–29 and 60 and above) and two time periods (1972–1982 and 2002–2017). The variable *ln_grain_prod.lag* is the grain production (in millions of dollars) at the beginning of the time period, and *grain_ch_pct* is the percentage change in grain production during the time period. Two dummy variables are included at the change of -100 percent and 0 percent, for the 2002–2017 data analysis. The results suggest that these effects may be heterogeneous across age groups and time periods.

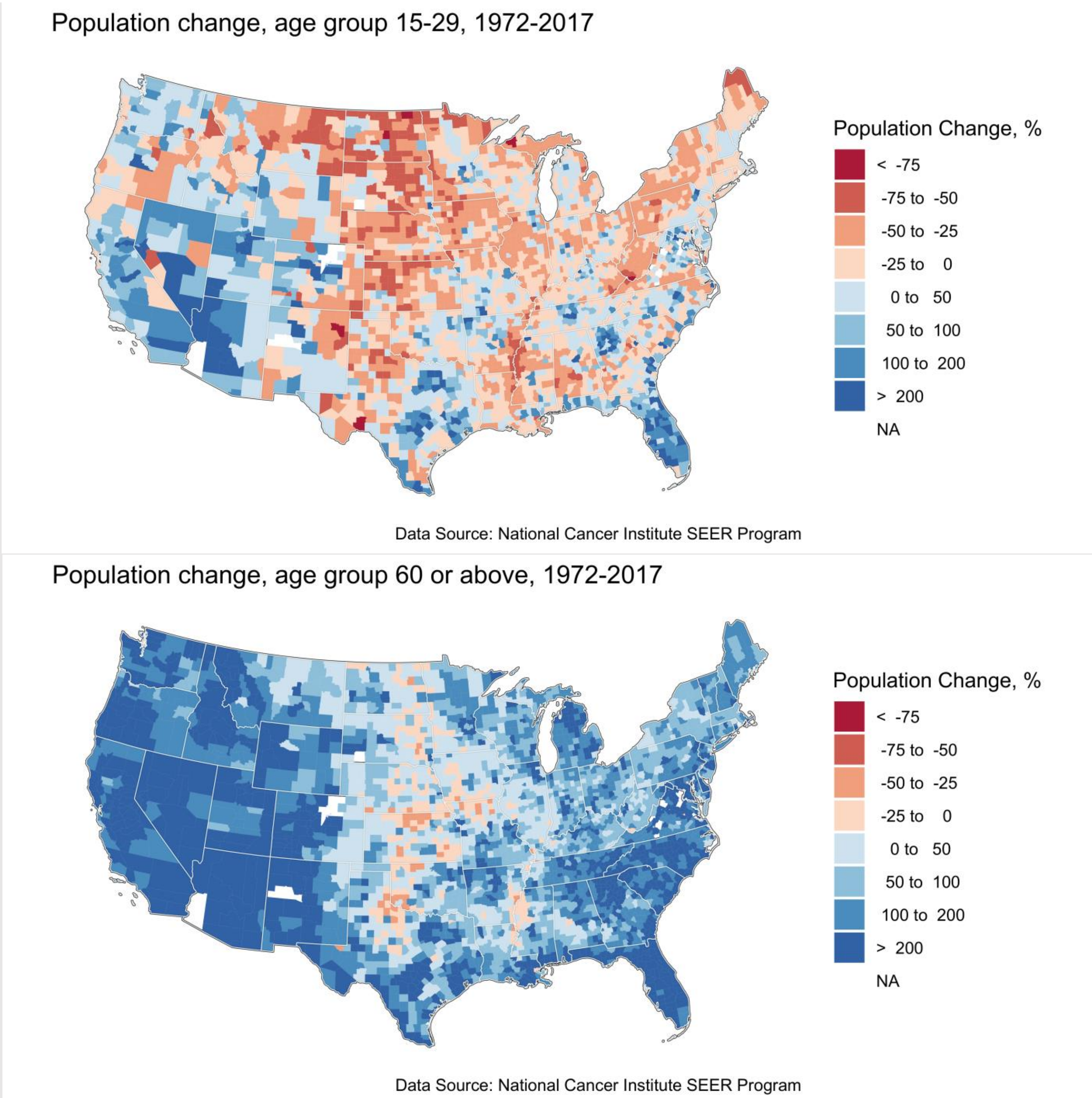


Figure 18. Population Change for Selected Age Group and Time Period

Table 3. Estimate of Grain Production and Population Change for Selected Age Group and Time Period

Variable	Population change, %			
	Models			
	(1)	(2)	(3)	(4)
Log of grain production, 1972	-2.740***	-1.918***	-0.665*	-5.548***
(ln_grain_prod.lag)	(0.273)	(0.251)	(0.342)	(0.593)
Change in grain production	-0.012***	-0.003	-0.011**	-0.016**
(grain_ch_pct)	(0.005)	(0.004)	(0.005)	(0.008)
Indicator for zero grain production			-4.493***	-3.854
(grain_ch_pct == 0)			(1.377)	(2.388)
Indicator for ceased grain production			-1.799	-3.406
(grain_ch_pct == -100)			(1.365)	(2.367)
State fixed effects	Yes	Yes	Yes	Yes
Sample age group	15–29	60 and up	15–29	60 and up
Sample Period	1972–82	1972–82	2002–17	2002–17
Observations	2,719	2,719	2,761	2,761
Adjusted R squared	0.26	0.374	0.111	0.307

Note: Statistical significance $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Models (1)–(4) are estimated on different subsets of data in terms of age group (15–29 for models (1) and (3): 60 and up for models (2) and (4)) and sample period (1972–1982 for models (1) and (2): 2002–2017) for models (3) and (4).

To analyze such effects systematically, we arrange a grid of subsamples by age group and time period and apply the same estimation model to each subsample. We use five age groups (0–14, 15–29, 30–44, 45–59, 60 and up) and four time periods (1972–1982, 1982–1992, 1992–2002, 2002–2017). In a `tibble` data frame, which is a special case of the `data.frame` class, one can split the data by a categorical variable via the function `nest()` and store such subsets of data in a list-column. We then apply a regression formula to each row of the data-column and store the results in another list-column.

```
# create the age group and time period combination
df_pop_grain <- df_pop_grain %>%
  mutate(age_era = paste0(age_group2, ":", Year,sep = ''))

# create a regression function to be applied to a given data.frame
pop_ch_model <- function(df) {
  lm( pop_ch_pct ~ ln_grain_prod.lag + grain_ch_pct +
          grain_ch_pct_0 + grain_ch_pct_neg100 + St_name, data = df)
}

# function to run a model by group via nest()
run_model_by_group <- function(df, group_var, model_as_function) {
  group_var <- enquo(group_var)
  df2 <- df %>% group_by(!!group_var) %>% nest()
  df2 %>% mutate(
    model = map(data, model_as_function),
    rlt   = map(model, summary) %>% map(coefficients) %>% map(data.frame),
    varname = map(rlt, rownames),
    estimate = map(rlt, ~ .x$Estimate),
    st_error = map(rlt, ~ .x$Std..Error),
    t_stat = map(rlt, ~ .x$t.value)
  )
}

lm_pop_age_era <-
  run_model_by_group(df_pop_grain  %>%
                       filter(!is.na(age_group2), Year >= 1980),
                     group_var = age_era,
                     model_as_function = pop_ch_model)

lm_pop_age_era %>% print(n = 5)
## # A tibble: 20 x 8
## # Groups:   age_era [20]
##   age_era            data model  rlt      varname  estimate st_error t_stat
##   <chr>     <list<df[,43> <list> <list>   <list>   <list>   <list>   <list>
## 1 age_0-14…  [2,719 × 43] <lm>   <df[,4]… <chr [4… <dbl [4… <dbl [4… <dbl …
## 2 age_0-14…  [2,799 × 43] <lm>   <df[,4]… <chr [4… <dbl [4… <dbl [4… <dbl …
## 3 age_0-14…  [2,802 × 43] <lm>   <df[,4]… <chr [4… <dbl [4… <dbl [4… <dbl …
## 4 age_0-14…  [2,761 × 43] <lm>   <df[,4]… <chr [4… <dbl [4… <dbl [4… <dbl …
## 5 age_15-2…  [2,719 × 43] <lm>   <df[,4]… <chr [4… <dbl [4… <dbl [4… <dbl …
## # … with 15 more rows
```

Here, column *data* is a list-column containing different subsets of the data separated by age group-era combination. List-column *model* contains the corresponding regression outputs, which are summarized in another list-column *rlt*, which are further isolated into list-columns of variable names, point estimates, standard errors, and *t* statistics. Each cell in the *estimate* list-column contains a list of coefficient estimates for a given subsample. These coefficient estimates can be extracted by function *unnest()*, which returns a long-format data frame that stacks coefficient estimates for various subsamples according to the age group-era combination.

```
rlt_age_era <- lm_pop_age_era %>%
  select(age_era, varname, estimate, st_error, t_stat) %>%
  unnest(cols = c("varname", "estimate", "st_error", "t_stat"))
rlt_age_era %>% print(n = 5)
## # A tibble: 905 x 5
## # Groups:   age_era [20]
##   age_era       varname           estimate st_error t_stat
##   <chr>         <chr>                <dbl>    <dbl>  <dbl>
## 1 age_0-14:1982 (Intercept)        0.391    2.25     0.174
## 2 age_0-14:1982 ln_grain_prod.lag -2.56     0.282   -9.05
## 3 age_0-14:1982 grain_ch_pct      -0.00711  0.00476 -1.49
## 4 age_0-14:1982 St_nameAR          7.26     3.00     2.42
## 5 age_0-14:1982 St_nameAZ         22.6      5.85     3.86
## # … with 900 more rows
```

For selected coefficients, we summarize the results in Figure 19. The plot on the left shows that people of all ages, the baby boomer generation in particular, moved out of grain-producing rural counties throughout the period spanning 1972–2017. The plot on the right shows that an increase in grain production was associated with a population decline from 1982 to 1992 and post 2002, across age groups.

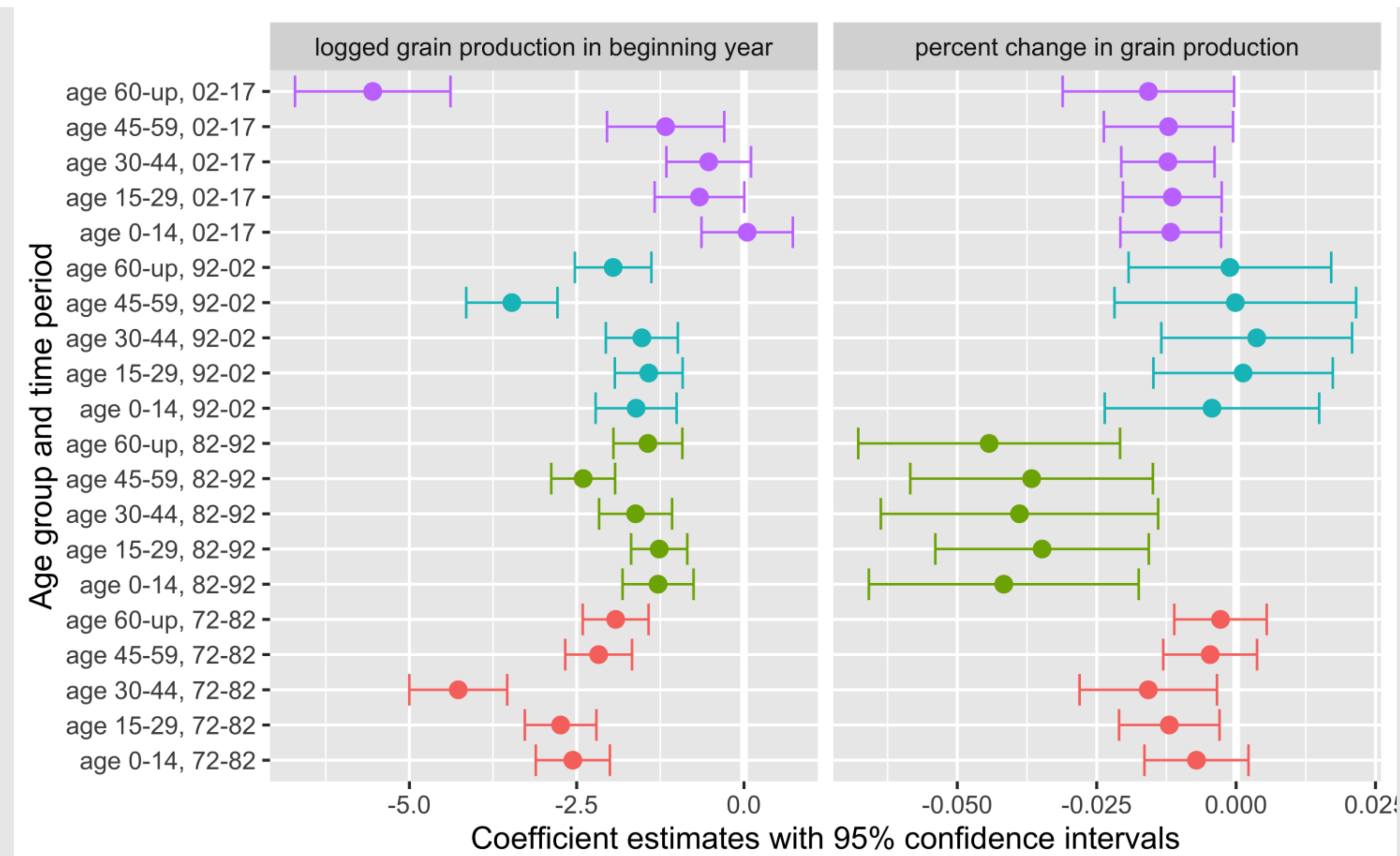


Figure 19. Associations between Grain Production and Population Change by Age Group and Time Period

Note: A OLS regression model is estimated for each subset defined by the combination of age group and time period. The plot shows the coefficient estimates for logged grain production in the beginning of the time period (left) and percentage change in grain production (right).

While the issue of rural depopulation is beyond the scope of our analysis here, it helps to shed light on the associations between grain farming and population change. Many rural communities were initially developed because of the land's potential to produce grain and support the residents. As grain production intensified with time, farms got bigger and fewer, and the communities that relied on grain farming shrunk.

6 Additional Tools

In this section, we briefly describe additional R tools that may be of interest to applied economists.

6.1 *rmarkdown*

The *rmarkdown* package allows for producing documents that combine text, R code, and the output of the code all in one place. It also accommodates LaTex math symbols and equations. Its output can be produced in several file types such as HTML, PDF, and Microsoft Word. *rmarkdown* can be useful for taking notes during data analyses, preparing lab reports, or drafting technical manuscripts. A template is available in RStudio Integrated Development Environment (IDE).

6.2 *flexdashboard*

As a special case of *rmarkdown* document, the *flexdashboard* output class allows one to easily assemble a dashboard-style layout consisting of separate segments of output panes. For example, multiple plots and tables can be arranged in columns and rows all in one screen. A *flexdashboard* template is available in RStudio IDE.

6.3 *shiny*

With *shiny* package, one can develop interactive applications that can run on local computers or be deployed online. A template is available in RStudio IDE. To learn more, a good place to start is [a tutorial by RStudio.](https://shiny.rstudio.com/)[12]

6.4 *dygraphs*

With the *dygraphs* package, one can create interactive time-series plots on which the user can see values associated with selected data points with mouse-over actions and select a time pan of the plot to zoom in and out. Here is a simple example that is plotted in Figure 20:

```
library(dygraphs)
load(file="ts_milk_price.RData")

PA <- ts_milk_price %>% filter(state_alpha == "PA") %>%
  select(Value) %>%
  ts(start = c(1990, 1), end = c(2019, 08), frequency = 12)

CA <- ts_milk_price %>% filter(state_alpha == "CA") %>%
  select(Value) %>%
  ts(start = c(1990, 1), end = c(2019, 08), frequency = 12)

cbind(PA, CA) %>%
  dygraph(main = "Monthly Milk Price, $/cwt") %>%
  dyRangeSelector()
```

[12] https://shiny.rstudio.com/

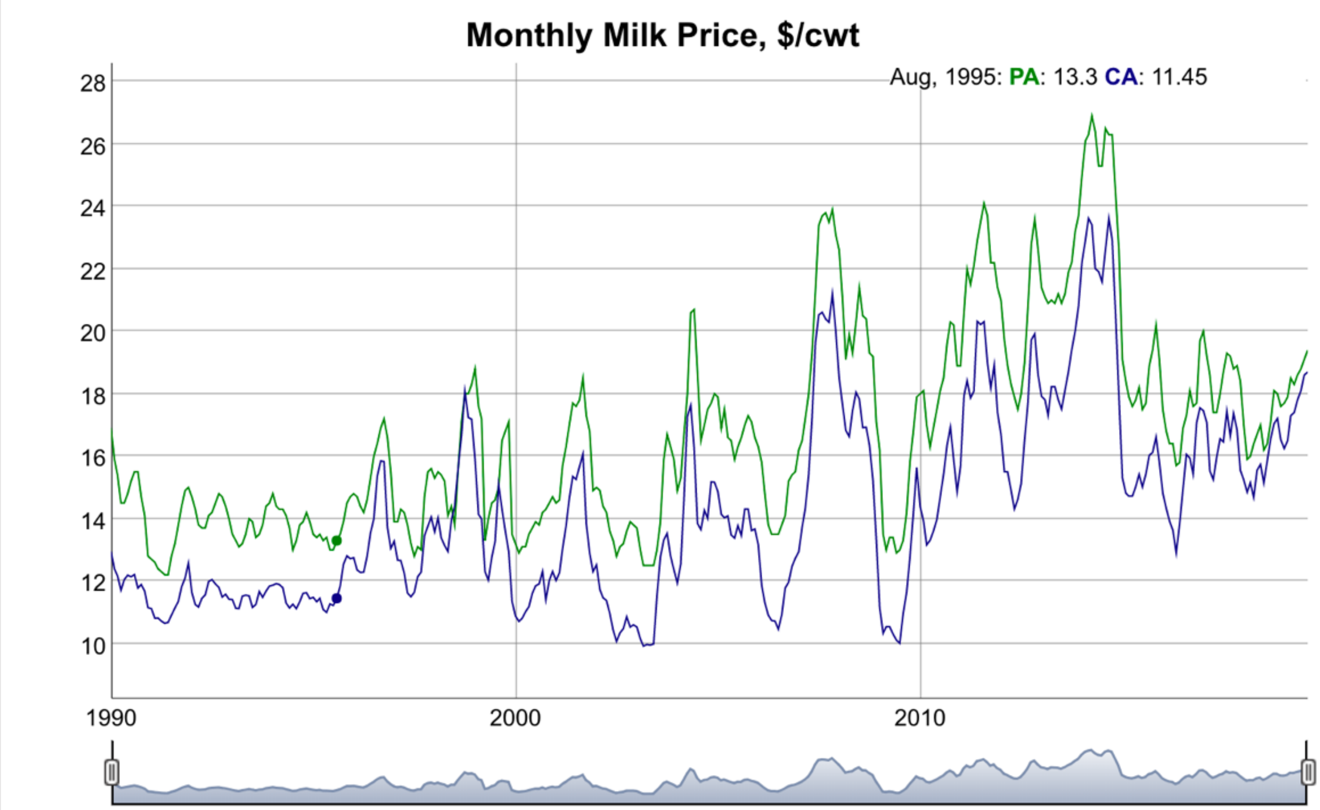


Figure 20. Example of an Interactive Dygraphs Plot for Pennsylvania and California Monthly Milk Prices

6.5 *leaflet*

The leaflet package lets one create interactive maps that can be hosted online with base maps provided by OpenStreetMap and CartoDB. Figure 21 was developed with data from the U.S. Agricultural Census to show the distribution of farms across the conterminous United States that reported using value-added marketing methods in 2017.

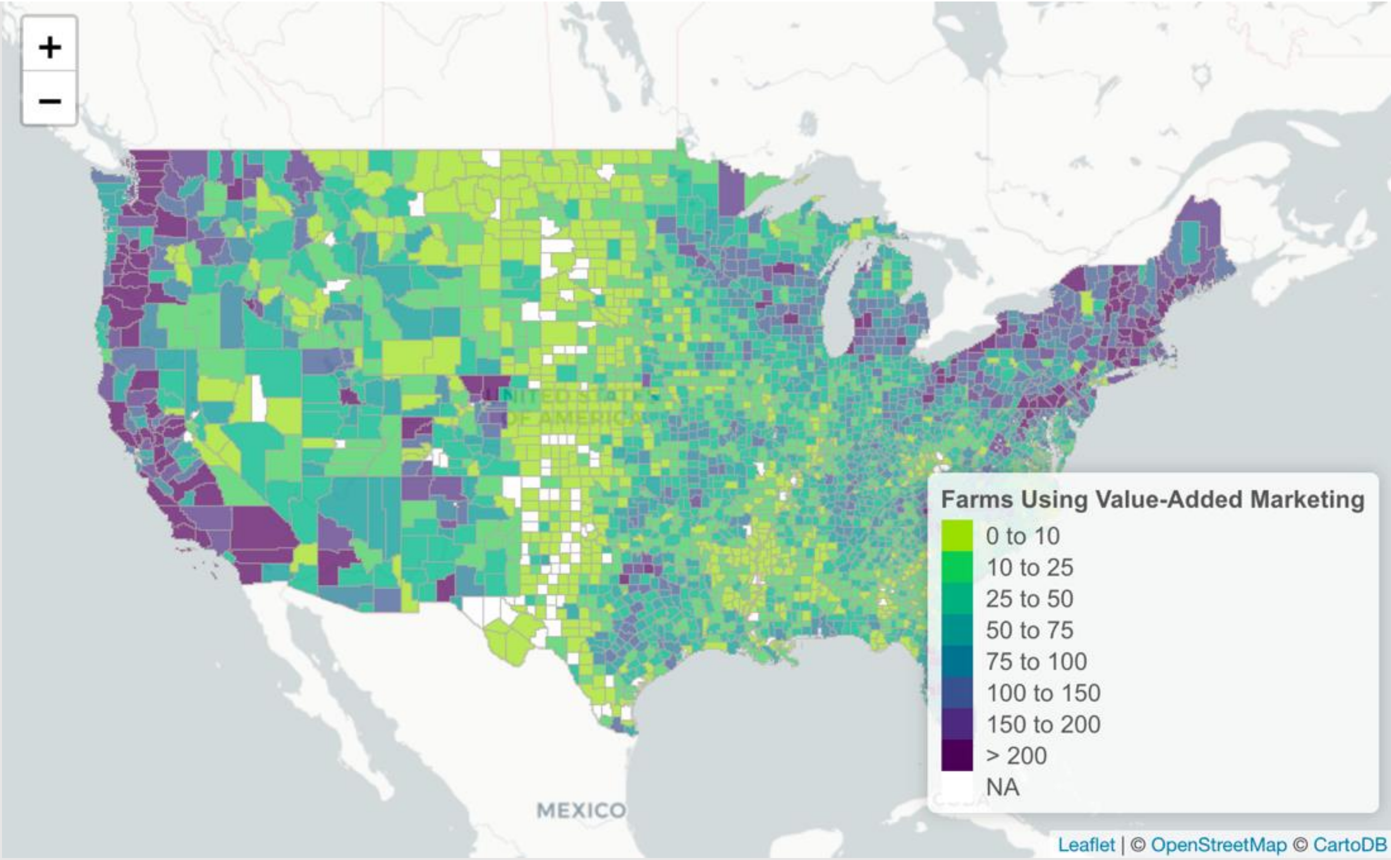


Figure 21. Example of an Interactive Leaflet Map That Allows for Zooming In or Out and Selecting the Area in View

6.6 Cheatsheets

We recommend all readers to explore [a collection of cheatsheets hosted by RStudio](https://rstudio.com/resources/cheatsheets/).[13] The cheatsheets provide great summaries of popular R packages and their examples. R beginners would find the cheatsheets about R-programming basics and RStudio IDE useful. Experienced R users may encounter recently uploaded and noteworthy packages for popular topics such as big data management, machine-learning, and integration with other programming environments.

6.7 Online Searches

R users quickly learn that the best way to find programming information or to get help is through online searches. A keyword search usually turns up relevant online Q&A discussions, which work remarkably well for troubleshooting (e.g., with fine-tuning data plots).

6.8 *data.table*

Although this article focuses on the *dplyr* package for data transformation, a popular alternative is the *data.table* package. For example, the following code performs the parallel tasks with some of the *dplyr* code we presented above (i.e., selecting the census table that contains the number of farms by farm sales class and also aggregating them into a binary farm sales class). Note the differences in the syntax of the two packages.

The reader may find that the syntax of *data.table* is not as readable as that of *dplyr*. Indeed, the developer of *dplyr* intentionally designed its syntax to be easy to read. Interested readers may be referred

[13] https://rstudio.com/resources/cheatsheets/

to online discussions[14] or side-by-side comparisons.[15] Also, notice the use of the same piping operator *%>%*, which in fact belongs to the *magrittr* package (from which *dplyr* imports it). An advantage

```
library(data.table)
library(magrittr)

us17_dt <- data.table(us17)
us17_dt[census_table == 2 &
      grepl("COMMODITY TOTALS - OPERATIONS WITH SALES", Item) &
      !is.na(Class),
     c("Class", "Value")]

county17_dt <- data.table(county17)
county17_dt[
    census_table == 2 &
    grepl("COMMODITY TOTALS - OPERATIONS WITH SALES", Item) &
    !is.na(Class) & Co_name! ="NULL",
    class_S_NS : = ifelse(Class %in% class_S, "S", "NS")] %>%
  .[, .(Value = sum(Value, na.rm = T)),
    by = c("St_code", "St_name", "Co_code", "Co_name", "class_S_NS")] %>%
  .[class_S_NS =="S"] %>%
  .[order(-Value)] %>% head(n = 10)
```

of *data.table* over *dplyr* is its computational speed, which can become important for large data sets (say, greater than 1 GB). For those who prefer the *dplyr* syntax but want the speed of *data.table*, try a package called *dtplyr*, which is currently being developed by the developer of *dplyr* package as a *data.table* backend for *dplyr.*[16]

6.9 *sparklyr*

Recent progress in the R and Spark integration now enables one to use R for processing so-called big data (e.g., in a distributed data file system like Apache Hadoop or in a streaming data platform like Apache Kafka). With the *sparklyr* package,[17] one can combine the core EDA techniques through the *dplyr* and *ggplot2* packages with large-scale data processing in Apache Spark, without holding the data in the local machine's memory. Put simply, *sparklyr* connects an R session with Spark, translates *dplyr* functions into Hive SQL code, and submits the code to the Spark connection. One can read a subset of data or data summary, generated by such *dplyr* data transformations, into the local machine's memory by the *collect()* function for data visualization by *ggplot2* . Moreover, the *sparklyr* package provides additional functions to utilize Spark's machine-learning library APIs, integrate a shiny application with big data, and build a data pipeline (e.g., a sequence of data cleaning, transformation, modeling, and prediction), which can be further exported as an API using the *mleap* package.

[14] https://stackoverflow.com/questions/21435.
[15] https://atrebas.github.io/post/2019-03-03-datatable-dplyr/.
[16] available from https://github.com/tidyverse/dtplyr.
[17] One can practice many functionalities of the `sparklyr` package with a simple local installation of Spark, without any access to an actual big data connection. For more information, see https://spark.rstudio.com/ and https://therinspark.com/.

7 Concluding Remarks

We have reviewed the core tools of data visualization and exploration from the recent developments in R freeware. We believe this new generation of tools would be a great asset for economists and students in applied economics. Hands-on learning with such tools can be highly complementary to many of economics courses, and given today's high demand for data scientists, it is valuable for students to acquire practical skills for EDA. In addition to their knowledge of statistics and econometrics, many students would be empowered to learn how to explore real-world data and become capable of generating effective data narratives and new hypotheses.

To advance students' skills in data analyses and cultivate their interests in economic issues, we suggest three directions of future efforts. First, teaching examples and case studies on EDA education may be shared through teaching journals, like this publication. Second, to aid instructors who undertake such teaching, applied economics departments may dedicate some tutorial hours for EDA and hire experienced students as peer tutors. Third, applied economics conferences may host undergraduate competitions for data visualization projects, which focus on public education and outreach rather than research outputs. On the last point, the hurdle for creating data visualization materials or data narratives is much lower, compared to producing new research findings, and therefore such projects will be able to engage a larger body of students. While it may not be called research in itself, the creation of insightful data plots can contribute to public knowledge, and hence it would merit recognition in applied economics communities. Through the combination of hands-on-learning, technical support, and academic recognition, EDA education can be made an integral part of an applied economics curriculum.

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Teaching and Educational Methods

Interacting with Agricultural Policy 280 Characters at a Time: Twitter in the Classroom

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JEL Codes: A22
Keywords: Social media, networks, pedagogy, education, Twitter, teaching of economics

Abstract
This article describes how Twitter can be used as a pedagogical tool to increase student engagement with agricultural policy both inside and outside of the classroom. This assignment, which can be tailored by instructors to meet learning objectives for a variety of course levels, can be used specifically to bridge the gap between economic graphs and real-world applications. In addition to increasing student familiarity with current events and real-world application of agricultural policy, the Twitter assignment requires students to operate on every level of Bloom's taxonomy with a focus on students' creativity and critical analysis skills.

1 Introduction

In a course that discusses agricultural policy, students will analyze the economic effects of tariffs, quotas, and subsidies. They will calculate and identify consumer surplus, producer surplus, and deadweight loss. What students may forget in a sea of graphs and calculations is the human element behind the policies. Who created the policy? Why did they create the policy? Who are the winners? Who are the losers? Who are the special interest groups? Answering these questions provides a fresh perspective to students that brings the graphs and calculations into focus as students see how the policy applies to real-world events.

The purpose of this article is to describe how Twitter can be used as a pedagogical tool to increase student engagement with agricultural policy and current events both inside and outside of the classroom. I use Twitter as a pedagogical tool to promote higher levels of thinking in both an Introduction to Economics course and a 400-level Agricultural Policy course to bridge the gap between economic graphs and current events. Students become actively engaged with agricultural policy by creating tweets that relate to current events and course material. The Twitter assignment has increased classroom participation and interest in the course material, while developing students' higher-order thinking skills.

1.1 Why Twitter?

Twitter is an open, social microblogging platform that allows users to share 280 characters of text, known as tweets. Users may also attach hyperlinks, images, and video to each tweet. Twitter allows for asymmetric user relationships in that users can be followed without following the same users back.

Twitter is a social media platform of choice for many because of its ability to keep users up-to-date with the latest news and the fact that close to half of Americans ages 18–24 are Twitter users (Perrin and Anderson 2019). While SnapChat and Instagram, social media platforms used to share photos, videos, text, and drawings, attract more college-aged students, these platforms are less likely to have regular users that report policy related to course materials (Shearer and Matsa 2018).

In previous versions of the courses, course assignments were focused on exams, quizzes, a term paper, homework, and a series of current event articles posted on the learning management system for each unit. Although students were expected to review the current event articles because they would appear on exams and quizzes, I found that students were not reading the articles with any sense of regularity. The Twitter assignments were devised as a way to encourage students to consistently interact with current events as they related to the class. Based on qualitative comments, students appear more confident in connecting current events based on assessment questions using Twitter.

2 Twitter in the Classroom

Twitter in the classroom has been well documented in the higher education teaching literature. In a seminal study on Twitter in higher education, Junco, Heiberger, and Loken (2011) found that using Twitter in an introductory seminar generated a deeper discussion of course content as compared with a traditional in-class student experience. My initial interest in using Twitter in the classroom stemmed from an article discussing how it was used in a project in a higher education geography course (Anderson 2017). In economics, the literature specific to Twitter centers on its use as an alternative to disseminating information through a learning management system (Al-Bahrani and Patel 2015; Al-Bahrani, Patel, and Sheridan 2017). Similar studies have been conducted in other disciplines (e.g., Elavsky, Mislan, and Elavsky 2011; Gikas and Grant 2013). Kassens (2014) is one of the only studies in economics to use Twitter as a writing assignment. She noted that Twitter assignments can improve writing skills in economics through forced efficiency via Twitter's character limit since students must focus on quality over quantity, improving focus on the key issues.

2.1 Twitter Assignment Overview

Each student selects an agricultural policy leader or organization to focus on and tweet about from their perspective for the duration of the assignment (for instance Sonny Perdue as a leader or American Farm Bureau as an organization). They create an account with an instructor-approved handle, and their tweets are only visible to their Twitter followers, which are restricted to the instructor and the class. The assignment can be varied depending on the length of the course/unit. For example, a student in the 400-level policy course may be required to tweet a minimum of three times a week for eleven weeks. Students in an introduction to economics course may be required to tweet over a shorter number of weeks to satisfy the Farm Bill unit.

Students are instructed to construct tweets from their leader/organization's perspective given course material and current events, and include links to relevant articles with a tweet of how they think their leader/organization would react to the article. They are also required to interact on Twitter with other students in the course on a weekly basis by replying to their peer's tweets.

The assignment(s) counts for between 8 and 15 percent of their final grade, depending on the length of the project, and serves as a creative alternative to a traditional term paper. Tweeting regularly throughout the semester translates into a moderate-length term paper depending on the required tweets per week. An advantage of the assignment over a traditional paper is that students are required to engage with the course content consistently rather than in a shorter chunk of time. The consistency of the interaction with the material builds policy fluency, in which students can quickly recall the information necessary to discuss the current state of agricultural policy. This is an important skill that can be used in job market interviews with agricultural agencies, crop insurance providers, and agribusiness companies.

As a result of the tweets, students develop a repository of resources to discuss in class. I use examples from recent student tweets as class starters or to create a Twitter poll based on current events. A rubric is provided to students that outlines exemplary work related to content, interaction with classmates, and course themes (see Supplementary Appendix). The instructor requirements associated with this assignment are: (1) initial setup of approved leaders/organizations, (2) monitoring the content of tweets, and (3) grading the tweets based on the rubric. Compared with traditional assignments, the overall time required for this assignment is similar, while the benefits to both students and the course are greater. Course instructions for students are included in the Supplementary Appendix.

2.2 Pedagogy/Learning Objectives

The learning objective for students is to become actively engaged with agricultural policy by creating tweets that reflect policy leaders' responses to current events and course material. This creative assignment engages students in both analytical and evaluative thinking. Students are not searching for the right answer; rather, they are extending course information as it applies to their knowledge of their leader/organization to address current events. The assignment requires students to analyze the material, make decisions, and create an end product that demonstrates understanding of both course material and their leader/organization.

Students also develop a fluency with current events and course concepts since they are consistently required to connect course material to current events. The frequent tweets can serve as a method of retrieval practice for students as they are consistently building their base of core knowledge related to course content. The value of retrieval improves long-term learning and retention (Agarwal, Bain, and Chamberlain 2012). Similarly, Blessing, Blessing, and Fleck (2012) found that frequent tweets using course material can improve student learning.

This assignment engages students in higher-order thinking. To successfully complete the assignment, students must generate tweets based on current events and class content, compare and contrast the views of leaders, critique a Twitter user's argument, and create an accurate representation of a leader/organization's voice.[1] The assignment works because students are not expected to respond with the "right" answer; they are extending course information as it applies to their knowledge of their leader/organization to address current events in an original way.

2.3 Developing Twitter Identities

I created a master list of Twitter accounts that students could use to select their Twitter identity. The list is composed of both agricultural leaders and organizations. Students signed up for their Twitter identity using a Google spreadsheet. Students are not allowed to use their personal Twitter accounts for the assignment, and the Twitter handle must follow a standardized format (e.g., LeaderFirstInitialLastNameClassName). Students may only follow the instructor and their classmates.[2] The class selects a profile picture/banner to display on all Twitter accounts associated with the project, and a class hashtag is chosen to easily track all course tweets. The student's Twitter account privacy settings must be changed to protect the user's tweets so that only followers can see the tweets.

Students are required to create a predetermined number of original tweets per week in addition to interacting with a peer at least one time per week. Retweets do not count as an original tweet since they do not require the student to comment on the information. Bloom's spiraling, a process of starting at lower levels of Bloom's taxonomy and steadily increasing the level of thinking required to compose tweets, can be used to scaffold the assignment.[3] For example, students are encouraged to start the project tweeting about where a leader is, what they are working on, and who they are meeting as they track their leader/organization on Twitter and/or the news. This builds confidence and increases familiarity with their leader/organization's voice. As the project progresses, students are encouraged to find articles and construct tweets related to how they think their leader/organization would react to the article to reach higher levels of Bloom's taxonomy.

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[1] To help students connect to their leader/organization's voice, students complete a Twitter Voice assignment prior to the start of the Twitter assignment. The assignment can be found in the Supplementary Appendix.

[2] Students are encouraged to look at their tweets daily, but following the actual leader could draw attention from the actual leader and cause them to report the account as a bot or fake or the account could be suspended for impersonation. This is largely avoided because accounts are kept private, but I err on the side of caution here.

[3] Bruner (1960) originally coined the term spiral curriculum.

The following are examples of student tweets resulting from the assignment:

Example 1:

Leader 1: *The Trump administration's proposed cuts to the SNAP program will leave 1 million children ineligible for free school lunches. They are unlikely to get the nutrition that they need at home. We should be giving more children the opportunity for free lunch, not taking it away.*

Reply to Leader 1 by Leader 2: *With efforts to try to cut back spending, many people like the elderly and children will be greatly affected. The proposal's main focus should not be on saving money, but on helping those it will affect.*

Reply to Leader 1 by Leader 3: *I agree that children and the elderly need to be helped, but where are the adult children/parents? If they are not willing to help themselves (working a job or 2—and saving money), why should the government? Requirements for SNAP should be changed regarding work requirements.*

Example 2:

Leader 4: *The hemp and cannabis industry is bringing young people back into agricultural jobs.*

Reply to Leader 4 from Leader 5: *As the market for hemp grows on a yearly basis, the number of young farmers is surely going to continue to rise.*

Reply to Leader 4 from Leader 6: *In the Senate, I worked to secure language for the legal cultivation of hemp. We must continue to work to protect the farmer's right to diversify their crops.*

Reply to Leader 4 from Leader 7: *Hemp is sparking the interest of young farmers. Information is still gathered on the eligibility for crop insurance and other payment programs. The THC level in the crop is a determining factor that has to be regulated.*

As students become more comfortable tweeting, their confidence with course material increases as they develop a more solid and consistent Twitter voice based on their selection. In addition, the Twitter assignment offers students an alternative to participating in large classroom environments. I have seen students who were initially reluctant to share their opinion in class exceed the required number of tweets for the assignment, a signal that the assignment generated interest above and beyond its requirements. While this is certainly not a guaranteed outcome, it does provide an important potential benefit of using Twitter in the classroom.

The effectiveness of Twitter in the classroom will vary depending on its purpose and use. Since 2017, I have used this assignment in five sections of two courses: an introductory agricultural economics course and a 400-level U.S. agricultural policy course with an intermediate microeconomics prerequisite. Below I offer guidance for instructors considering implementing Twitter in a policy specific course, but many of the recommendations are appropriate for any assignment using Twitter.

2.4 Challenges

Using Twitter in the classroom has presented the following challenges: (1) class hashtags, (2) how to evaluate tweets, (3) retweeting, (4) user names, (5) framing the assignment, (6) banners, and (7) protect tweets.

1. Initially, I did not require students to use a course hashtag (e.g. #AG 400) with every tweet. This made tracking the class tweets more challenging since I follow more than students.
2. Second, assessing the tweets presents the typical grading challenges in terms of addressing participation, quality, and engagement with peers.
3. Third, without any tweeting restrictions, many students began to retweet without comment (e.g., copy a tweet from someone else with nothing additional added).
4. Fourth, usernames were initially not standardized, and students chose names that could be confused with the actual person.
5. Fifth, I initially framed the assignment as an activity separate from class discussion, creating missed opportunities for students to connect the assignment to course ideas.

6. Sixth, I did not standardize course banners/profile pictures, and some students chose backgrounds/profile pictures that were the same as their chosen leader/organization.
7. Seventh, I did not require students to protect their tweets, and this made it hard to restrict discussion to the class.

2.5 Recommendations for Challenges

The challenges outlined in section 2.4 are based on my first attempt incorporating Twitter in the classroom. I update the assignment each semester to address new challenges, provide clearer directions, and/or change expectations. Below are recommendations for instructors using Twitter for the first time.

1. Require students to use a course hashtag on every tweet (e.g. #AG 400). The primary benefit of the hashtag is to connect the instructor with students and allow students to easily find their peer's tweets. In addition, the hashtag makes it easy to search tweets from the course and track assignment participation. The course hashtag ends when the course ends.
2. Create a rubric that clearly describes your expectations regarding participation, quality of tweets, and engagement with peers. The rubric in the Supplementary Appendix emphasizes the requirement that the tweets reflect course themes to signal to students the importance of satisfying this element of the assignment. The rubric also outlines the minimum number of tweets required weekly and for the course. If you do not set a weekly minimum, some students may delay tweeting until the last two weeks of the assignment. If students have created a Twitter account for this assignment, it is straightforward to search their Twitter feed and observe the dates that they posted. Last, use Twitter lists to help you group students together so you can more easily track their posts.
3. Do not allow students to retweet as part of their total tweeting requirements. Retweeting without comment does not align with the purpose of the assignment and does not generate further discussion with peers. Emphasize to students that each tweet should be related to course themes in the voice of the leader/organization. The student must compose a tweet that explains why an article was chosen and/or how they think their leader/organization may respond.
4. Require a standard username each semester. I did not do this the first time I ran the assignment, and students chose names too close to the actual leader/organization. In addition, some students used their personal account, and this is problematic since the tweets may not reflect their personal views but can be seen by their followers.
5. Use student tweets in class. This helps students view the assignment as part of the course rather than as a separate assignment. Use their tweets to start a class discussion. Use the articles they have tweeted about as required reading for discussion forums. Create exam/quiz questions based on the twitter conversations. Instructors can create both formative and summative assessments based solely on student tweets.
6. Require students to use a standardized course banner and profile picture. This signals to anyone that sees the tweets that the account is for educational purposes only. The profile picture could be standardized as the school's mascot for added clarity.
7. Require students to change their privacy settings to protect their tweets so that only followers can view their content. Since the students are tweeting as if they are leaders/organizations, it is important that people outside of the class cannot see the content. We do not want students to interact with the larger Twitter community.
8. Require students to write a reflection after the Twitter assignment ends. This allows students to reflect on the course themes they connected to current events while also tracking their interaction with peers. It also provides valuable information that can help improve the assignment for future students.
9. Show students' techniques for detecting bias in sources. This helps students make sure that the source they are using in their tweets is reliable and helps put "fake news" in a clearer context. Examples of resources to enhance digital literacy are the CRAAP test (Lewis 2018) and the Check, Please! Starter course (Caulfield 2019).

3 Conclusion

The Twitter assignment is a pedagogical tool to promote higher-order learning. Using Twitter creates a strong connection to course material and builds agricultural policy fluency. To successfully complete the assignment, students must operate on every level of Bloom's taxonomy: they must identify and define concepts, summarize content and rewrite tweets in their own words, generate tweets using current events and class content, discuss the views of other leaders in comparison to their tweet, critique a peer's tweet, and create an accurate representation of their leader/organization's voice.

All assignments carry benefits and costs, and the Twitter assignment is no different. Using Twitter in the classroom may result in changes to your syllabus, as you respond to a trending topic in class. While this can make the class challenging to prepare for, it is worth it to build policy fluency and connect students to the graphs and calculations necessary to compare and contrast policies. The assignment is suitable for small to mid-size classes (roughly 65) even without the help of a teaching assistant. The time required to grade the assignment is similar to what is required to grade a term paper of similar length, especially with the use of a class hashtag and standardized student account names.

For courses that discuss agricultural policy, the Twitter assignment is a good option because of its ability to connect students with both the course content and their peers. Students noted that the assignment led to a deeper understanding of the material, kept them involved with current events, exposed them to different points of view, and made them feel more prepared for class. Incorporating Twitter into a course also provides students with sources for continued learning as they have a list of leaders/organizations they can track following the conclusion of the course.

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Teaching and Educational Methods

Making Business Statistics Come Alive: Incorporating Field Trial Data from a Cookstove Study into the Classroom

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Abstract
This paper describes how to incorporate data from a randomized controlled trial in rural Uganda into teaching an undergraduate business statistics course. The semester-length classroom exercise includes discussions and brainstorming sessions, which allow students to imagine how they would execute a field experiment and analyze the data. Students become familiar with one data set as they use it to supplement textbook examples of hypothesis testing, analysis of variance applications, and simple linear regression. The article discusses the background of the sustainability challenge of 2.8 billion people in the world cooking with solid fuels, the rollout and schedule of integrating field-experiment data into the classroom, and student evaluations of the exercise. The target audience is undergraduate statistics students and/or instructors interested in demonstrating how textbook statistics are used to better understand a real-world sustainability challenge.

1 Introduction

As instructors, how do we make required classes interesting for students? Can we engage students who may feel they are forced to be in a required class (as opposed to an elective they choose)? Is there a way to make statistics come alive for students who say they don't like statistics? Personally, how do I teach statistics in a way that is fun for me? As a new faculty member, these were the questions I asked myself when I was assigned to teach multiple sections of undergraduate business statistics. In this paper, I outline my attempt to answer these questions by integrating data from a development economics experiment from Uganda into the classroom.

The course I was assigned to teach is called "Statistical Decision Making" and is the second of two semester-length classes, which compose the statistics requirement for undergraduate business majors at Fordham University. The recommended textbook for these two courses is Introduction to Business Statistics by Ronald M. Weiers (Weiers 2010). Typically chapters 1–7 (topics from the visual description of data to continuous probability distributions) are covered in the first semester, and the second course covers chapters 8–16 (topics from sampling to linear regression). The majority of students taking the second-semester course are sophomores.

Because numerous sections of this class are offered every semester, there were teaching materials (including PowerPoint slides and practice questions) available within the department. As a new faculty, I did not want to alter the core of what was already being taught, but I did want to develop lectures that incorporated statistics in action with real world (nontextbook) applications. Additionally, pedagogical literature suggests that incorporating experimental design into statistics courses leads to better learning outcomes, especially as data science skills become more important to potential employers (Anderson-

Cook and Dorai-Raj 2001; Blades, Schaalje, and Christensen 2015; Hardin et al. 2015; Rossman and Chance 1999).

For these reasons, I made the reimagining of a field experiment I was a part of in Uganda a recurring part of the class. In this paper I show how—as the statistical concepts in the textbook grew more complex—I used the field experiment data as the basis of empirical examples of the statistical techniques successively presented in the textbook chapters.

2 Cookstove Experimental Problem Background

Around 40 percent of the world's population (2.8 billion people) cook on traditional cookstoves that burn solid fuels such as wood, charcoal, or animal dung (Bonjour et al. 2013). The burning of these solid fuels is associated with many sustainability challenges. For example, the smoke from these stoves kills approximately 4 million people each year (Lim et al. 2012), as well as contributes to deforestation (Bailis et al. 2015) and global warming (Bailis, Ezzati, and Kammen 2005; Bond, Venkataraman, and Masera 2004; Ramanathan and Carmichael 2008). Furthermore, the time costs of gathering fuel and the burden of diseases caused by breathing in cook fire smoke typically falls on women and children, potentially increasing existing gender inequalities (Patrick 2007; Edwards and Langpap 2012).

2.1 A Potential Solution

The safest cooking for consumers requires cleaner fuels such as gas or electricity (which is typical in most of the developed world). However, because of limited infrastructure, high costs, and related supply chain challenges (Lewis and Pattanayak 2012; Rehfuess et al. 2010), these cleaner fuels are not readily available for much of the 2.8 billion people that use solid fuels in developing countries. Therefore, one option that may be beneficial (at least until infrastructure improves) is fuel-efficient cookstoves. These cookstoves are designed to use the same types of solid fuels, but are engineered to burn more completely and create less smoke (because of an insulated burning chamber and better air flow), reducing some of the associated environmental and health risks.

2.2 An Adoption Puzzle

While fuel-efficient cookstoves may reduce the amount of fuel necessary to cook (saving the user time and/or money collecting or purchasing fuel, while reducing health risks from less smoke emissions), this does not necessarily mean that fuel-efficient cookstoves will be adopted readily by any given culture or people group. In fact, leading research about the adoption of fuel-efficient cookstoves notes that given the potential benefits of cookstoves, most regions continue to adopt fuel-efficient stoves at "puzzlingly low rates" (Mobarak et al. 2012). It is this adoption puzzle that is the focus of the field experiment that I used in the classroom to illustrate various statistical concepts as the semester progressed.

2.3 The Field Experiment

The randomized controlled trial that is the focus of the class exercise (Beltramo et al. 2015b) was executed in the Mbarara region of southwestern Uganda. In this experiment we examined two central hypotheses: (1) if low willingness to pay for a cookstove was because of low awareness of the health, economic, and time-savings benefits of fuel-efficient cookstoves and/or (2) if low willingness to pay was because of limited access to financing.

We held sales meetings in 36 different communities in Mbarara. About 60 participants came to each sales meeting. When participants arrived (the meetings were usually held on a soccer field), each participant completed a survey on their cooking practices, household socio-demographics, employment, and other information. After the intake survey was completed, we randomly assigned participants to one of four groups corresponding to one of the four informational marketing messages: (1) health benefits of the new stove, (2) time and money savings of the new stove, (3) both of those messages combined, and (4) a control group with no informational message. Each of the four groups went to a different corner of the soccer field, and an enumerator delivered their informational message using a script and flipcharts. The control group held a discussion—led by an enumerator with flip charts—on common cooking practices while the other groups received their informational marketing messages.

Once the messages were delivered, everyone came back to a central area, and saw a demonstration of the Envirofit G3300 stove, cooking common local dishes. The manufacturer of the Envirofit reports that it reduces biomass fuel consumption by up to 60 percent versus a three stone fire, reduces smoke and harmful gasses by up to 80 percent, reduces cooking time by 50 percent, and has a product lifespan of 5 years (Envirofit Inc. 2014). We then ran two sealed second-price auctions for the Envirofit G3300. In both auctions, everyone who wanted to bid wrote his or her bid on a piece of paper and put it in an envelope. The winner of the auction won the stove but paid the price of the second highest bidder (see additional details on the auction setup in Beltramo et al. (2015b)).

The two auctions differed in the terms offered. One offered a typical "cash and carry" offer, which means that the highest bidder would pay the second-highest bid, and at the time that the payment was made, the buyer would receive the stove. The second auction required the winner to pay the second-highest bid for the stove, but that total was due over four equal weekly installments. The buyer received the stove when the first of the four payments was made. The vast majority of participants placed bids on both the "cash and carry" and the "pay over time" offers.

2.4 Results of the Field Experiment

More than 2,100 people participated in the auctions for the Envirofit stove. An overview of the results of the field experiment was that there were no statistically significant differences in average bids when comparing average bids between the four randomly assigned informational messages. This suggests that a lack of information about the time savings or health benefits of clean cooking technologies does not appear to be a barrier to willingness to pay (i.e., demand).

Interestingly, however, we found that when participants bid on the pay over time offer (four equal payments spread over four weeks), they bid an average of 40 percent higher than when they bid on the cash and carry offer (pay all at once). This appears to lead to the broader conclusion, that at least in this setting, relieving liquidity constraints is much more important than relieving informational constraints (Beltramo et al. 2015b; Levine et al. 2018). These findings have important implications for how organizations such as the Global Alliance for Clean Cookstoves allocate scarce resources to promote the adoption of fuel-efficient cookstoves and would suggest that resources should focus on financing and relieving liquidity constraints rather than informational marketing campaigns. We executed other field experiments in this Ugandan context as well, while those experiments are not the topic of this paper, readers can consult them to delve deeper into the topic of cookstoves, the local background, and/or the results (Beltramo et al. 2015a; Beltramo et al. 2019; Harrell et al. 2016; Simons et al. 2014; Simons et al. 2017). Next, I describe how I integrated the field experiment examining how informational marketing messages affected willingness to pay into the classroom.

3 Classroom Integration

In the "Statistical Decision Making" course, we cover chapters 8–16 of Weiers (2010). The main topics for the semester are sampling distributions and estimation, hypothesis testing, and an introduction to linear regression. The reimagining of the cookstove field experiment fits nicely into these broad topics, as designing the field experiment allows students to recreate a real-life sampling exercise. It also provides real-world data to do many different hypothesis tests, and the underlying data set can also be used when introducing simple regression analysis.

3.1 Overview of the Semester Plan

To create the setting to challenge students to develop policies for fuel-efficient cookstove demand, I first conduct a large brainstorming exercise. The two key questions for the brainstorming exercise were: "What are the biggest problems facing the world today?" and "Why do we study statistics?" This is a fun and engaging exercise as we write all of the students' suggestions on the board. Once 15–20 ideas are up on the board, I group the items and narrow the discussion toward poverty, health, and climate change–related issues. This follows with an open-ended discussion as to why we study statistics. My intention in discussing both of these questions as part of the same conversation is for students to begin to grapple with the larger question of how do we know what we say we know, and can statistics help us be more confident in what we know?

Next, I present the following scenario to the classroom. The Global Alliance for Cookstoves, which has the ambitious 10-year goal to foster the adoption of clean cookstoves and fuels in 100 million households, approaches our class and asks for help with the following:

- What is the best way to create demand for fuel-efficient cookstoves?
- How can we know that we have created demand?
- Design a program and data collection plan that will give us evidence to answer these questions.

Once these questions are posed to the class, we break into small groups to discuss/brainstorm further. Each group comes up with their best ideas and then I write each of those ideas up on the board.

Generally some group recommends some type of informational marketing lessons to teach about the benefits of the stoves and/or a group recommends some type of financing to make the stoves more affordable. Building upon the student recommendations, I describe what we did in the field (laid out in Beltramo et al. (2015b) and the supplementary teaching notes).

At this point, I illustrate the mechanism of the second-price auction. I bring freshly baked brownies to the classroom and auction them off using the same sealed second-price auction mechanism that we used in the field. By doing this I show students that the researcher can map out the entire demand curve based on all the bids that were submitted while only selling one cookstove (or set of brownies).

Next, I detail how I used the cookstove auction data collected in Uganda to give students the opportunity to practice the statistical techniques learned in the course (e.g., t-test vs. population means, t-tests with two sample means, hypothesis tests with two samples, ANOVA tests with more than two samples, etc.). The data I used in the classroom is provided in the supplementary teaching materials (described in detail in the next section). Additionally, data and code has been deposited online with other related publications (e.g., Beltramo et al. 2015b; Simons et al. 2018).

3.2 Semester Schedule

Detailed teaching notes and sample PowerPoint slides are provided in the supplementary materials, which outline how the cookstove experiment is integrated into the course. See Table 1, for a summary of how the topics of the chapters in Weiers (2010) and the topics illustrated with the cookstove data line up.

Table 1. Integration of Cookstove Study by Topic

Ch.[a]	Topic	Integrating the Cookstove Study	Supplementary materials provided
---	Introduction	Large brainstorming exercise asking "What are the most important problems facing the world today?" and "Why do we study statistics?"	None—chalkboard-based classroom discussion
8	Sampling Distributions	Show YouTube video from the Global Alliance for Cookstoves (GACC). Introduce the premise of the field experiment—the GACC has approached our classroom and asked us to design a study to answer: (1) What is the best way to create demand for fuel-efficient cookstoves? and (2) How can we know that we have created demand?	Stove Preliminary Setup Slides.pptx
9	Estimation from Sample Data	Describe the field experiment from Beltramo et al. (2015b). In the experiment, we tested four informational marketing messages: (1) good for your health, (2) saves time and money, (3) both messages combined, (4) no message (control group) to see if lack of information was a barrier to willingness to pay for a cookstove. We also tested financial constraints, by allowing participants to bid both on cash and carry offer (get stove at the same time you pay full amount) and a pay over four weeks offer (get stove with first payment, then additional three installment payments one week apart). In class, we do a sealed second-price auction for some homemade baked goods; this allows the students to go through the same bidding procedure as the participants in the field experiment.	Experimental Rollout.pptx
10	Hypothesis Tests with Sample Mean or Proportion	How representative is the sample of 2,100+ respondents that was gathered in rural Uganda? I found population level information about Uganda (from World Bank, Uganda Communications Commission, Uganda Bureau of Statistics) on self-employment, cell phone ownership, age of household head, and household size. Then we use hypothesis tests to compare the sample means from the Uganda cookstove data with these population figures.	Hypothesis Tests—sample vs population.pptx

Table 1. Continued

Ch.[a]	Topic	Integrating the Cookstove Study	Supplementary materials provided
11	Hypothesis Tests with Two Sample Means or Proportions	Now we can answer one of the main questions we designed the experiment to answer, is there a difference in mean bids between the control group, which did not receive any information, and the mean bid for the group that received information on the health benefits of the stoves? Students choose the appropriate test and then calculate the appropriate z or t statistic to test that hypothesis. They can do hypothesis tests with any two of the four informational marketing treatments. However, they do not yet know how to compare all four at the same time.	Hypothesis Tests—two samples.pptx
12	Analysis of Variance Tests	Once we have learned ANOVA, we can compare the mean bid of all four informational marketing messages. Students create the hypothesis, calculate the F-test statistic associated with the ANOVA analysis, and use it to decide whether the average bids were statistically significantly different between informational marketing messages or not.	ANOVA—means of four samples.pptx
13	Chi-Square Applications	I did not use the cookstove data for a chi-square example, though data is provided so an instructor could create a topical example if desired.	None
14	Nonparametric Methods	I did not use the cookstove data for a nonparametric methods example, though data is provided so an instructor could create a topical example if desired.	None
15	Simple Linear Regression and Correlation	In the ANOVA chapter, we examined the difference of the mean bid between the four informational marketing messages. Next, we analyze if there is a different average bid for those who bid on the pay now versus the pay over time offer. To do this, I show the students how we could model this with a hypothesis test (like in Ch. 11), or we could show it with a basic regression setup. After we have introduced the concept of a basic regression (Ch. 15), we run a simple linear regression to see the difference between the average bid of pay now versus pay over time bids.	Regression—difference in payment offers.pptx
16	Multiple Regression and Correlation	Show students that we can add variables to the right hand side of the regression (move from simple linear regression to multiple linear regression). In this way, we can answer questions like what is the difference in average bids between the two payment offers while controlling for age, gender, and/or family size. I also have additional slides prepared to wrap up various questions students may have raised over the semester regarding cookstove adoption and use (based on Beltramo et al. 2015b; Beltramo et al. 2019; Levine et al. 2018; and Simons et al. 2017).	Conclusion—stove adoption and use.pptx

[a] Chapters are out of the textbook by Weiers (2010).

3.3 Student Responses

In general, students enjoy the experience of going through the cookstove study throughout the semester. The majority of students say they like the integration in that it brings real data into a course that often just uses textbook examples. Some meaningful student quotes about the course and integrating the cookstove study include:

> *I just wanted to reach out and say thank you for a great semester! You made stats more than just bearable . . . you made it fun! I am someone who dreads math but got lucky having you as a professor. I appreciated your real world material as it made the content more meaningful. I am an individual who always wants to make a positive impact, so I was happy to see that even in fields like statistics, you can change the world.* —Sophomore
>
> *I transferred to Fordham exactly for courses like this that combine social justice initiatives with academia. As evident by my grade, I hate numbers. However, I hope for a career that will help change the world, and you showed me that data and stats are essential to this mission.* —Junior
>
> *To me, being able to learn about a chapter, then look at a formula and map out how you used this specific formula while you performed your studies made the class much more interesting. This was not only good review for the class, but it also showed that the information we were going over was very powerful and can make a serious impact on the lives of millions of people throughout the world. For the majority of classes I've had at Fordham, one of the biggest drawbacks for me is the inability to relate the material to something that I know will be useful once I graduate. However, you were able to present the material in a way that proved what we were learning is useful and is actually used when analyzing data after performing experiments.* —Sophomore
>
> *Cookstoves made my least favorite subject a highly tolerable subject.* —Sophomore

Although these comments from students are encouraging, not all students were completely on board with the exercise. Some student comments were critical about the exercise. The most common critical comment was that students felt the example dragged on too long (i.e., the whole semester) or was not applicable to their immediate experience.

> *Would like more interesting/applicable problems. Slightly redundant slides/examples.* —Sophomore

Additionally, it seemed most students were interested in the topic, but some wanted to know the results of the experiment immediately as opposed to the schedule where little by little was revealed as we covered additional topics in the textbook.

3.4 Discussion

In response to these critiques, I began to group and condense the cookstove material. I have taught this cookstove integration in ten sections of this course, and the first couple of times I taught it, I tried to mention the cookstove example (even very briefly) in every class meeting. I have since pooled the cookstove material with the plan of discussing it more in depth when I discuss it, but only once per chapter (once every two to three class periods as opposed to every class meeting). Although this still does not solve the issue if a student simply does not find the example interesting or compelling, it does make the material feel less disjointed. When students say they want to know the results of the field experiment immediately, I generally pivot the discussion saying that the experience of research is slow and that we will uncover the results as we learn additional statistical techniques to do so.

3.5 Extensions

At the end of the semester, I like to take a full class session to review what we learned through the integration of the cookstove experiment into the course. When doing this, students generally ask many questions that fall outside of the scope of the informational marketing experiment described in Beltramo et al. (2015b). Some of those questions usually are: We saw in the cookstove examples that informational marketing was not effective in increasing demand, but that an offer to pay over time was effective. Was there anything else you found to be effective to raise demand for the cookstoves? Do people use the new cookstoves once they receive them? Did the donors appreciate your study? How did they use the information you created? and other questions. To address these questions, I describe the related studies that we performed in Uganda on creating demand for cookstoves and how stoves are used over time by the households (Beltramo et al. 2015a; Beltramo et al. 2019; Levine et al. 2018; Simons et al. 2017).

This also allows for a discussion of the history of cookstove programs more broadly in the developing world. The progress of these programs has been uneven (Barnes et al. 1994; Gill 1987; Maes and Verbist 2012; Smith et al. 1993), with critiques suggesting that programs failed because of a lack of linking the cooking technology with the explicit needs of the cooks that use the devices. Framing an in-class discussion with this historical context of mixed success can be the basis of an in-depth discussion on cookstoves and the challenge of sustainability topics more generally.

If time allows, another valuable discussion is around the interpretation of a negative statistical finding. For example, in the data used in the classroom exercise, there was no statistically significant difference between bids across the four informational marketing messages. How should researchers interpret this? Does this mean that participants already knew the benefits of fuel-efficient cookstoves? Does it mean that many of them were not fully convinced of the benefits outlined in the marketing messages? Were their interests in cookstoves generally low and their bids did not properly reflect their true valuation? Was the sample large enough to provide statistical power? In the context of the hypothesis tests developed, are negative findings equivalent to no result? A broader discussion incorporating these questions gives the instructor an opportunity to demonstrate how to carefully assess the meaning of negative and null findings.

4 Conclusion

In this paper and the supplementary teaching materials, I describe how to integrate a development economics field experiment about an important sustainability issue into the ongoing structure of an undergraduate business statistics course. I found that doing this made the course more fun to teach for me, and more engaging for the students as well. Part of this was likely because this was a research topic I am passionate about. However, another part was that the field data collected fit very nicely into the typical structure of a statistics course where the topics get incrementally more complex as the course progresses. This allowed students to become familiar with one data set and to focus their mental energy on the statistical concepts as opposed to using that energy to learn a different data set as progressively more complex statistical techniques were introduced. Last, this exercise allowed students to grapple with the challenges of experimental design and see how statistics were used to better understand a real-world sustainability challenge.

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Teaching and Educational Methods

Convenient Economics: The Incorporation and Implications of Convenience in Market Equilibrium Analysis

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Abstract
Convenience is perhaps the most important "commodity" being sold in the market today, and yet there is nothing of analytical substance to be found in most undergraduate textbooks. The purpose of this article is to provide a straightforward framework for teaching students the economics of convenience, utilizing the standard tools of introductory and intermediate microeconomics. The framework is used to answer several questions related to convenience that could not be answered with the typical supply and demand framework found in undergraduate textbooks. The key analytical features of the article are provided in a complementary PowerPoint file in the online supplementary appendix.

The real price of everything, what everything really cost to the man who wants to acquire it, is the toil and trouble of acquiring it. —Adam Smith, Wealth of Nations

1 Introduction

One does not have to be an economic savant to recognize that we live in an "on-demand culture" (Fromm 2019) and "convenience is the ultimate currency" (Nielsen 2018). Everywhere you look companies are extracting economic rents from the mine of convenience: home robotic devices, voice-activated devices, virtual use devices, driver assisted technologies, finger print and face recognition access, online and automatic bill pay, personalized ads based on shopping history, and even price drop notification features online. Convenience is especially prevalent in the food sector: in-store ordering kiosks, personal checkouts at grocery stores, online food shopping and delivery or pick-up service, meal kit delivery services, a continuum of pre-prepared foods, and touchscreen smart refrigerators. One study estimates that, "on average consumers are willing to pay 11 percent more for each layer of convenience in the food chain in anything from online grocery delivery to restaurant take out" (Findling 2017).

Given the ubiquity of convenience in the marketplace, one would expect our textbooks to be replete with at least chapters or sections on convenience. That is not the case. Perusing some of the top selling undergraduate microeconomics textbooks reveals there is nothing of analytical substance on convenience (via Amazon: e.g., Mankiw 2012; Sowell 2015; Krugman and Wells 2018). This significant analytical gap is important because it leads to an inability of students to understand the economics of convenience; its implications on decision making and the standard variables of interest: market prices and quantities.

For example, here are just a few questions in the food sector that are difficult to address with the standard economics found in undergraduate texts but are easily addressed with the economics of convenience covered in this article.

- *Is store location more important than store prices in choosing a store?*
- *Why do single-headed households demand more convenience and eat out more than dual-headed households?*

- *How do transaction assisted devices affect markets?*
- *What is the common link between online, offline grocery markets, meal kits, and grocerants?*
- *Why are prices in food deserts higher than in nonfood deserts?*

The purpose of this article is to provide a straightforward framework for teaching students the economics of convenience utilizing the standard tools of introductory and intermediate microeconomics. The framework can be used to analyze the impact of convenience on market prices and quantities in a straightforward extension to typical supply and demand diagrams. Methodologically, a general Stigler and Becker (1977) framework is followed by incorporating convenience within a broader set of resource constraints from advanced consumer and retail supply theory. As the student should know, demand and supply analysis rests on the ideas of agents optimizing an objective(s) (i.e., utility, profit) subject to constraints. On the demand side, because there can be a preference for convenience, it needs to enter the utility function. However, time and effort are also limited resources, and given that convenience saves these resources, it also enters into constraints. On the supply side, given that consumers value time and effort, firms may seek to provide convenience and effectively shift the cost of inconvenience from the consumer to the firm. This must occur within the context of profitability (i.e., revenue and cost impacts).

The framework presented is methodologically progressive because it has "excess explanatory content" over explanations that appeal simply to preferences, behavioral biases, or irrationality (e.g., Lakatos 1993; Davis 1997). For example, the framework creates an intuitive link between classical economics and the exciting new field of nueroeconomics. Nueroeconomics "combines research from neuroscience, neurobiology, and economics [and] . . . provides parsimonious models of decision making capable of delivering qualitative behavioral predictions" (Brocas and Carrillo 2008 p. 175). By embedding several of the key concepts from nueroeconomics within an extended framework of standard tools, topics in nueroeconomics can be easily introduced and discussed with students because they become novel applications of well-known concepts.

The next sections define convenience, present the demand side, then the supply side, and then brings them together to analyze some of the previous questions. Given the target audience is a typical undergraduate course, convenience is incorporated within the context of a perfectly competitive model (supply and demand). It is certainly recognized that the appropriateness of this depends on a host of factors: the questions of interest, the market, the degree of spatial, temporal, and product aggregation, and so on. As such, the conclusions provide some discussions and guidelines for extending the analysis to imperfectly competitive settings. Finally, the key analytical features of the article are provided in a complementary PowerPoint file in the online supplementary appendix.

2 Defining Convenience in the Market

Convenience is normally defined as saving time, but it can also include saving effort, physical and mental. Two activities can require the same amount of time but very different effort levels. A 15-minute walk does not require the same effort as a 15-minute run, or shopping online for an hour does not require the same effort as shopping offline for an hour. The importance of recognizing both physical and mental effort in economic analysis has a long history, especially in the study of wealth and labor.[1] Mental effort has been called "psychic cost" (e.g., Sjaastad 1962; Ingene 1984; Rosen 1986), or within the fields of behavioral economics and nueroeconomics, it is closely related to the concept of cognitive load (e.g., Sweller 1988; Camerer, Loewenstein, and Prelec 2005).

Starting from the basics, all economic transactions require four steps: (i) *information acquisition* (e.g., who, what, where, how much), (ii) *payment acquisition* (e.g., in-kind, cash, credit, electronic), (iii) *good acquisition* (e.g., at purchase, delivery), and (iv) *possible good transformation* (e.g., used as input into

[1] Early economic textbooks, such as Marshall (1920) and Taylor (1913) and more recently Becker (1985) all included discussions of both time and effort. For example, Marshall (1920, p. 76) states, "the theory of wants can claim no supremacy over the theory of efforts." Taylor (1913, p. 1) states, "it is a fact obvious to everyone that wealth is a thing which absorbs a very large amount of our time, thought, and effort."

producing something else). Convenience is considered "the ultimate currency" because, like a currency, it is absent or present in each of these steps. And each of these four steps requires labor, both in time and effort, by both consumers and producers, and this is how convenience enters the market. Consequently, at each step there are potential opportunities for both consumers and producers for saving time and effort. Because time and effort are valuable resources, they have associated with them implicit opportunity costs and thus value in being saved.

3 Demand Side

With this background, a theory that incorporates convenience both in the utility function and in the resource constraints is desirable, and Nobel Laureate Gary Becker's (1965, 1985) Household Production Theory (HPT) is well suited for this task.

On the preference side, Becker's HPT is based on the observation that individuals do not get utility directly from *goods* purchased in the market, but rather use these goods as inputs, in combination with other inputs (e.g., time and effort), to produce *commodities* that give direct utility (i.e., step four above). This is a very old idea dating back to Bentham (1963), who identified 15 basic pains and pleasures the individual produces (e.g., warmth, shelter, nutrition, safety, etc.).

On the constraint side, students should know the core concept of allocative efficiency: a resource is allocated for an objective efficiently (without waste) via a (cost) price system. In undergraduate classes we tend to focus only on money, but time and effort are two equally important constraints. Specifically, based on the computational view of the brain from psychology (e.g., Edelman 2008), the concept of allocating limited cognitive resources is now well established in the literature (e.g., Alonso, Brocas, and Carrillo 2014; Kool et al. 2010; Kool and Botvinick 2014). Any decision task will have associated with it a cognitive load. A high cognitive load task requires more cognitive resources than a low cognitive load task (e.g., doing your taxes vs. doing your nails). Cognitive load plays a key role in the utilization of cognitive resources and also in the dual system view of the brain. Dual system processing consists of a fast system (system 1) that uses little cognitive resources and a slow system (system 2) that uses more cognitive resources (e.g., Kahneman 2011).[2] The basic principles of allocating a scarce resource then apply whereby perceived benefits and costs are compared. One of the main findings in this literature is that many decisions are made in the context of trying to conserve cognitive resources so there is a tendency to use the fast system for decision making if possible, *ceteris paribus*. Consequently, the inclusion of an effort constraint is a parsimonious and intuitive way to connect the standard toolbox to the neuroeconomics literature.

Along these lines, Becker (1965, 1985) defines the *full income constraint*, which can consist of money, time, and effort. Associated with the full income constraint are *full prices* that consists of two parts: a direct price and an indirect price. Recall in the context of a constraint, the price represents how much of a resource must be given up (the opportunity cost) to get one unit of the good or activity. The direct price is simply the price associated with the money constraint. However, for any other resource constraint, such as time and effort, there will be an indirect or shadow price as well.[3] The student will probably recognize the idea of a full price, if not the name, if they are familiar with the economics of a negative externality, such as steel production generating pollution. In that context, the marginal social cost of pollution is an indirect cost of steel, and when added to the market price, gives the full cost of steel production. In the typical supply and demand graph, this will be shown as a shift up in the supply curve that is attributed to the marginal social cost of pollution per unit of steel produced. This idea can be generalized for distinguishing between the market price and the full price and is a powerful general construct that allows for incorporating many other types of costs within the typical supply and demand

[2] Davis and Serrano (2016), chapter 10 provide much more detailed development and discussion of dual system decision making in a food context.

[3] A closely related broad term for indirect costs not priced in the market is transaction cost, but the transaction cost literature tends to focus on the implications for industrial organization not households (see Pollak 1985).

diagram. However, the incorporation needs to be done in a non-ad hoc and theoretically consistent fashion that extracts all the potential explanatory power and applications.

More formally, let i denote the individual, j the location, and k the good. Utilizing an undergraduate version of Becker's (1965, 1985) model, the individual i receives utility from K *commodities* $Z_{ij1}, Z_{ij2},\ldots,Z_{ijK}$. In a food context, obviously one of the commodities could be a meal. The commodities are produced by the individual using *market good inputs* $Q_{ij1}, Q_{ij2},\ldots,Q_{ijK}$, own *time inputs* $T_{ij1}, T_{ij2}, \ldots, T_{ijK}$, and *effort inputs* $E_{ij1}, E_{ij2}, \ldots, E_{ijK}$. In a slight generalization of Becker's (1965) basic model, the commodity production technology has the form:

$$Q_{ijk} = a_{ijk} Z_{ijk} \tag{1}$$

$$T_{ijk} = b_{ijk} Z_{ijk} \tag{2}$$

$$E_{ijk} = c_{ijk} Z_{ijk} \tag{3}$$

A unit of Z_{ijk} produced requires a triplet combination of goods, time, and effort. The *technology parameters* a_{ijk}, b_{ijk}, and c_{ijk} for converting goods, time, and effort into commodities are individual (i), location (j), and good/commodity (k) specific. As will be shown, this generalization proves very useful in analyzing several forms of convenience. The parameters b_{ijk} and c_{ijk} capture the idea of convenience in both time and effort. Specifically, b_{ijk} is the amount of time (the quantity), and c_{ijk} is the amount of effort (the intensity) required for individual i in location j per unit of Z_{ijk} produced. So, in this "household production" context, all the standard economic intuition from production theory related to biased technology change can be utilized because a change in the technology parameters a_{ijk}, b_{ijk}, and c_{ijk} can be thought of as technological change. Consequently, a *decrease* in one of these parameters means that *less* of the input (market good, time, or effort) is required to produce the same level of the commodity, and the new technology is input "saving." It is important to recognize that (2) and (3) refer to the *total* time and effort required, which may be composed of many categories that are added together, such as planning, travel, and shopping time/effort so the saving may occur in any one of these categories or several.[4]

Regarding the resource constraints, there are three: (1) an expenditure (money) constraint, (2) a time constraint, and (3) an effort constraint. The full income constraint is derived from recognizing that money income comes from converting both work time and effort into money via the labor market. This implies the two main constraints are time and effort:[5]

$$T_i = T_{iw} + \sum_j \sum_k T_{ijk} \tag{4}$$

$$E_i = E_{iw} + \sum_j \sum_k E_{ijk} \tag{5}$$

where T_{iw} and E_{iw} is the quantity of time and effort spent in market work, respectively. The full income constraint is then:

$$\sum_j \sum_k P_{jk} Q_{ijk} = W_i T_{iw} + R_i E_{iw} + V_i \tag{6}$$

where P_{jk} is the market price the individual faces in location j for the kth market good, and W_i is the individual's hourly wage rate or opportunity cost per unit of time. The variable R_i represents the dollar value for a unit of effort or the cognitive load. It is this term that links the standard toolbox with key

[4] Becker (1965) allows for this by using vector notation for the technology constraints.

[5] For the student, the notation Σ is the Greek letter for "S" and is just shorthand notation saying "S"um over all types of goods (the ks) and over all locations (the js).

concepts coming out of nueroeconomics.[6] The variable V_i is unearned income. Substituting (1) – (5) into (6) and rearranging yields the *full income constraint* expressed in *full prices* or:

$$Y_i = \sum_j \sum_k \Pi_{ijk} Z_{ijk} \tag{7}$$

where:

$$\Pi_{ijk} = a_{ijk} P_{jk} + b_{ijk} W_i + c_{ijk} R_i \tag{8}$$

is the *full price* of the commodity Z_{ijk} and $Y_i \equiv W_i T_i + R_i E_i + V_i$. The first term of the full price ($a_{ijk} P_{jk}$) represents the direct price, and the next two terms ($b_{ijk} W_i + c_{ijk} R_i$) represent the indirect price. Numerous economic insights are already forthcoming by taking a closer look at the full price and its components in equation (8).

3.1 The Full Price Principle

The same or lower full price does not mean the same or lower market price and vice versa. Because the full price consists of three separate components, there is an infinite number of combinations that can lead to the same or even lower full price. A high direct (market price) component (a_{ijk}, P_{jk}) can be offset by a low indirect component (b_{ijk}, W_i, c_{ijk}, R_i).[7] Alternatively, the same or even lower direct component (a_{ijk}, P_{jk}) can be offset by a higher indirect component (b_{ijk}, W_i, c_{ijk}, R_i) leading to higher full price. Knowing the value of the full price Π_{ijk} tells you nothing about any of the values of the subcomponents (a_{ijk}, P_{jk}, b_{ijk}, W_i, c_{ijk}, R_i) and vice versa.[8] Perhaps most importantly, the triple subscript notation implies these equalities or differences can be due to individual (i), location (j), or good (k) equalities or differences or some combination.

3.2 Some General and Specific Applications of the Full Price Principle

Consider then some general and specific applications of the full price principle. Comparing across goods, the principle implies two goods in different locations can have the same full price ($\Pi_{i11} = \Pi_{i22}$) but different market prices ($P_{11} \neq P_{22}$) because some other components of the full price differ (a_{ijk}, b_{ijk}, c_{ijk}, W_i, R_i).[9] In fact, many market options may not only have a lower indirect time price ($b_{ijk} W_i$) but also a lower indirect effort (cognitive) price ($c_{ijk} R_i$) such that an individual is willing to pay a higher direct (market) price ($a_{ijk} P_{jk}$) because the full price (Π_{ijk}) will be the same or even lower. This result is ubiquitous in the marketplace. For example, a common phenomenon that plays out every weekend all over the world is individuals go out to eat, walk into a restaurant without a reservation, and ask what is the wait time (que) for seating. If the que is too long, they go to another restaurant in hopes of a shorter que. Individuals will often be willing to pay more for the meal ($P_{22} > P_{11}$) if the que is shorter, and this is captured by the full price because the full price between the two restaurants can be equal ($\Pi_{i22} = \Pi_{i11}$) even though the time and effort prices differ. In a recent study De Vries, Roy, and Koster (2018) found that longer wait times relate to a longer time to customers returning, a shorter dining duration (i.e., trying to keep the full price

[6] Treating the cost of a unit of time and a unit of effort as not good/activity specific is a rather standard simplifying assumption that could be relaxed adding more complexity without a great deal more insight. The key point is the quantity of time and effort each has an implicit cost and one should not confuse the per unit cost with the quantity. Different activities certainly require different quantities of time and effort and so the *expenditure* per good/activity will differ.

[7] This is just an application of the concept of compensating differentials from labor economics dating back to Adam Smith (Rosen 1986).

[8] The astute student may recognize this as just an application of the more general algebra rule of more unknowns (six) than equations (one) being undetermined, and so nothing can be said about the values of the unknowns.

[9] It is likely the student has already been exposed to this idea in a strictly spatial setting if they have been exposed to the "law of one price" where once transportation costs are taken into account, the prices of the same product from two locations are equal. This is just a generalization of that concept.

low), and higher revenue for shorter wait times. The principle applies to any case where there are substitute products that have a shorter wait time: from semi-processed ingredients versus basic ingredients in a homemade meal (Yang, Davis, and Muth 2017) or delivery versus takeout. Another example would be search costs stemming from information searches as an example of the indirect price components. From this perspective, firms with good reputations or with well-known national brands and advertising reduce search costs and thus can have a higher good price but not a higher full price (Stigler 1961; Ehrlich and Fisher 1982; Pashigian and Bowen 1994). Other examples of this are ubiquitous as well. For example, even if you have enough expertise to do your own taxes, you may pay an accountant to do them because you view the full price as cheaper from the accountant than doing them yourself because you attach a high value to your time and the cognitive effort. You may pay more for a product online because once the time and effort costs are taken into account, the full price is cheaper than offline shopping. Other examples are a lawn service that cuts your grass, in-home cleaning services, and so on. Generally stated, an individual can be willing to pay a higher direct price if the indirect price associated with the good is lower, leaving the full price the same or even lower.

As the principle suggests, the logic works in reverse as well. Two market goods can have the same direct market prices ($P_{11} = P_{22}$) but different full prices ($\Pi_{11} \neq \Pi_{22}$) because some other components of the full price differ (a_{ijk}, b_{ijk}, c_{ijk}, W_i, R_i). For example, a grocery store across the street from your house versus one a mile away may have the same prices and indeed may be part of the same chain, but the one closer to home will have the lower full price simply because of the lower time cost. Marshall and Pires (2017) find that store convenience is a more important determinant of store choice than prices, lending support to the importance of full prices over good prices.

Although this is a useful result for comparing different goods or locations, it is perhaps even more useful for helping explain differences across individuals within the same household because the technology parameters are not only location and good specific, they are also individual specific. Consider then the case of a dual-headed household, where individual one is more productive than individual two in producing the commodity, say a meal ($b_{1jk} < b_{2jk}$). Even if all other elements of the component prices are the same, individual one will have a lower full price than individual two ($\Pi_{1jk} < \Pi_{2jk}$), and thus if the household is minimizing cost of production, individual one will produce the meal. In this context, the household may still consume a meal produced at home because individual one has a production technology that makes it cheaper than eating food away from home, *ceteris paribus*. Thus "no matter how the members divide family resources between the two members, each member agrees to choose the most efficient shopper [producer] for each of the goods that the family purchases . . . The efficient solution requires the member with the lowest minimized full price be the shopper" (Pashigian and Bowen 1994, p. 39). This is essentially just an example of the insights that production efficiencies can achieve by division of labor, as stated in the first sentence of *The Wealth of Nations* (Smith 2010), and provides insights on household organizational structure (Pollak 1985).

Note what this would imply for the lack of intrahousehold "trade" opportunities for single-headed households. In 1960, about 5 percent of households had only one person, and 9 percent of children lived in single-headed households. By 2018, these numbers were 30 percent and 27 percent, respectively (U.S. Census Bureau 2019). A single-headed household can only compare their full price of a meal at home to a meal prepared away from home, not to a perhaps cheaper full price from a partner. The theory would predict therefore that, *ceteris paribus*, single households would demand more convenience, spend less time at in-home food production, and eat out of the home more frequently, which is what has been found in the literature (e.g., Dave et al. 2009; Anekwe and Zeballos 2019; Byron 2019; and You and Davis 2019).

3.3 Demand Function and Curve

Proceeding to the demand function for the market good, first note that optimization of the utility function subject to this full income constraint leads to the demand functions for the commodities of the general form:

$$Z_{i11}^{D} = Z_{i11}(\underset{(-)}{\Pi_{i11}}, \underset{(?)}{\Pi_{i12}}, \ldots, \underset{(?)}{\Pi_{iJK}}, \underset{(?)}{Y_i}) \quad : \quad \textit{Individual Commodity Demand Function} \qquad (9)$$

The parenthetical sign under each variable indicates the direction of the relationship between the variable and the quantity demanded, so as the full price of commodity one Π_{i11} increases (decreases) the quantity demand of commodity one Z_{i11} decreases (increases), *ceteris paribus*. The question marks under the other full prices Π_{ijk} indicates the directional relationship will depend on if other commodities are substitutes (+ sign) or complements (- sign) and under the income Y_i if the commodity is a normal (+ sign) or an inferior good (- sign).

However, the main question of interest is how does convenience affect the market demand for the market good? Remember the underlying framework is household "production," and therefore, the market good is an input used in production of the commodity so the market good demand is *derived demand*. Furthermore, the interest is in how the different components of the full price affect the market demand for the market good, so we can proceed as follows. First, substitute the full price for good one from (8) into the individual demand function (9) and substitute the result into (1). Next, recall the market demand is an aggregation of individual demands, so drop the *i* subscript such that the variables will be market level variables. Finally, just let the bold variable $\boldsymbol{O}^D$ represent a list of all the other variables (a vector) not related to the full price of good one and the list would now include other full prices, income, population, and perhaps other factors, such as seasonal variables. The market demand for good one in location one can then be written in general form as:

$$Q_{11}^{D} = Q_{11}(\underset{(-)}{P_{11}}, \underset{(-)}{W}, \underset{(-)}{R}, \underset{(-)}{a_{11}}, \underset{(-)}{b_{11}}, \underset{(-)}{c_{11}}, \underset{(?)}{O^D}): \quad \textit{Market One Derived Demand Function} \qquad (10)$$

As seen from (8), all the components of the full price (P_{11}, W, R, a_{11}, b_{11}, c_{11}) will tend to increase the full price and, given the law of demand in the full price, anything that increases the full price will decrease the demand for the commodity and thus decrease the derived demand for the market input. This is the reason all the component variables have a parenthetical negative sign.

As Stigler and Becker (1977, p. 89) point out, a movement along the commodity demand function is captured by a shift in the market good demand function. Why?
Recall, demand curves show the relationship between own price and quantity demanded. A movement along the demand curve shows the relationship between the own price P_{11} and the quantity demanded Q_{11}. The change in some other variables, other than own price, is then captured by a shift in the demand curve or simply stated a change in demand. For example, if the time it takes to purchase a good increases, say waiting in line, the demand for the market good will decrease or shift to the left, *ceteris paribus*. More generally, if any of the other component variables (W, B, a_1, b_1, c_1) increase (decrease), the demand curve for the market good will decrease or shift in (increase, shift out), *ceteris paribus*.

4 Supply Side

On the supply side, especially retail supply, there are two important interrelated concepts that are associated with convenience economics: (i) economies of scale and scope and (ii) cost shifting.

4.1 Economies of Scale and Scope

Most students should be familiar with the concept of economies of scale. *Economies of scale* occur when cost per unit (average cost) decreases as the operation is scaled up or output increases. Economies of scale can occur for multiple reasons. It may be because of spreading out a fix cost, such as a machine. For example, once a printing press is bought, the *total cost per unit* to print 40 papers is much higher than to print 4,000 because the main additional cost is the paper and ink. Alternatively, it may be because of efficiency gains in repetition and specialization of laborers in their tasks or cost reduction associated with buying or processing bulk orders of inputs. *Economies of scope* exists when the average cost of producing two or more goods together in one place is less than the cost of producing them at separate locations. This can be because of specialized "knowhow" within the firm that can be utilized in all goods sold, or there is shareable input across the goods (Teece 1980; Panzar and Willig 1981), such as a production facility or simply some managerial or labor expertise. A car or guitar manufacturer may produce many different models that have a lot of the same common elements (e.g., engine size or guitar neck). A stocking or checkout clerk, and all the associated mechanization, can stock or checkout a can of soup just as easily as they can stock or check out a can of beans. Thus, the underlying total cost is relatively constant, but the average cost per item is decreasing because the number of items is increasing.

4.2 Cost Shifting

Retail supply theory provides a very intuitive way to handle convenience utilizing all the standard tools (e.g., Betancourt 2004; Bronnenberg 2018). In the basic supply and demand framework, prices and quantities are common variables to both the producers and consumers in decision making. Retail supply theory effectively extends this analysis to include the household technology parameters. The key is to recognize that the retailer can affect the technology parameters in the household production technology (a_{ijk}, b_{ijk}, c_{ikj}) by providing "distribution services" that are designed to change these technology parameters. This is known as *cost shifting* in the retailing literature because firms effectively take on some of the costs the individual would normally incur in the production of the commodity (e.g., Betancourt 2004, p. 8). Cost shifting can occur in any of the four basic transactions, ranging from simply providing the consumer some information, to delivering a good, to a central buying location, to more processing to make the good closer to a commodity. In the food sector, food delivery, bagged salads, meal kits, or any pre-prepared meal are all examples where the retailer incurs some of the cost the consumer would normally incur, in an effort to hopefully increase profits.

The cost of distribution services has long been recognized as implicit in the standard supply analysis, but are often overlooked.[10] Recall the price on the supply curve is the minimum price required to bring the good to the consumer and that must include all costs. Within a supply and demand diagram, the market clearing price and quantity occur where the good is sold, not just produced.

Cost shifting can be thought of as a form of technological change, which is often categorized as one of two types: (i) technology push or (ii) demand pull. Technology push is driven by an internal innovation of the firm designed to reduce the cost of production or distribution with no direct impact on demand. For example, reducing the number of checkout clerks by installing more self-checkout scanners, after paying for the scanners, would decrease labor costs and thus would be a technological push change. Alternatively, demand pull technology change occurs because of a perceived profit opportunity through a potential increase in demand and may be associated with an increase in cost (Kamien and Schwartz 1982, chapter 2). In the present context, a demand-pull innovation is a form of induced innovation. Induced innovation occurs when the high cost of a factor of production induces an innovation to reduce the use of that factor (Hicks 1932). In the present context, individuals' high time and effort cost induces firms to produce new time- and effort-saving technologies for individuals. Installing an in-store bakery and hiring bakers would be a demand push technological change.[11]

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[10] Marshall (1920), in his principles book, discussed the difference between the costs of production versus the cost of "acquiring" a market (Marshall 1920, p. 239). Chamberlain (1962) spends an entire chapter (chapter 5) discussing the difference between production costs versus selling costs, but as he discusses, the standard approach is to just consider selling costs as part of production cost as a simplifying assumption.

[11] More specifically, the self-scanners would be considered a process innovation and the bakery a product innovation. As Kamien and Schwartz (1982, p. 2) state, "likewise we shall not distinguish between process innovations and product innovations. Process innovations are technical advances that reduce the cost of producing existing products, whereas product innovations involve development of new or improved products. Equivalently, the former may be defined as upward shifts in

Formally, retail firms produce joint products: the explicit good and the implicit distributional services (Betancourt and Gautschi 1988; Betancourt 2004). Using a specification similar to that given by Ehrlich and Fisher (1982) and Pashigian and Bowen (1994), the household technology parameters can be made functions of three types of variables: (i) firm cost shifting services f_{ijk} that may be individual, location, and good specific, ranging from something as simple as delivery services to personalized ads, (ii) public good services g, such as a public transportation to get to a grocery store, and (iii) individual, location, good specific capital h_{ijk}, which may be physical capital, such as a car, but could also be human capital, such as education level or route knowledge to a store. Thus, using function notation we would have:

$$a_{ijk} = a_{ijk}(\underset{(-)}{f_{ijk}^{a}}, \underset{(-)}{g^{a}}, \underset{(-)}{h_{ijk}^{a}}) \tag{11}$$

$$b_{ijk} = b_{ijk}(\underset{(-)}{f_{ijk}^{b}}, \underset{(-)}{g^{b}}, \underset{(-)}{h_{ijk}^{b}}) \tag{12}$$

$$c_{ijk} = c_{ijk}(\underset{(-)}{f_{ijk}^{c}}, \underset{(-)}{g^{c}}, \underset{(-)}{h_{ijk}^{c}}) \tag{13}$$

The superscript letter signifies possible different targeted variables for each of the inputs (good, time, and effort). The parenthetical negative sign indicates that increases in these variables would decrease the individual consumer's technology parameters, which would in turn reduce the full price via equation (8) and cause an increase in demand (shift out in the demand curve).

Given that firms are construed as producing both the market good Q_{jk} and distribution services f_{ijk}, the firm's cost functions and thus supply curves have to reflect this multiproduct nature. Recall in the standard single good setting, the firm's supply curve is its marginal cost curve above the minimum of the average variable cost curve (short run) and the marginal cost depends on the quantity produced (movements along marginal cost) and input prices (shifts in the marginal cost). The multiproduct extension is straightforward, but there are multiple ways to write the multiproduct supply function that are theoretically consistent (Beattie and Taylor 1985, chapter 5). In the present context, the most transparent approach is to use a conditional supply function. In a multiproduct setting that allows for scale and scope economies, a conditional supply function will express the quantity supplied of one good as a function of its output price, the price of inputs used in its production, the quantity of the other goods produced (distribution services), and indicators of operation scale and scope.

The scale, scope, and cost shifting effects on the firm's supply curve will depend on how scale, scope, and production of the distribution services affects the marginal cost per unit of the market good sold. Increases in scale and scope would be expected to decrease marginal cost and thus shift the marginal cost curve out as these are technological push factors. Alternatively, increases in distribution service could be marginal cost increasing (e.g., hiring more service laborers), neutral (e.g., adopting a technology that only affects average cost, such as a Wi-Fi connection), or decreasing (e.g., creating more self-checkout lanes, decreasing labor cost) as these could be either technological push or demand pull factors.

4.3 Supply Function and Curve

Similar to the market level demand, the market level supply for good one in location one is an aggregation of individual supplies, so dropping the *i* subscript denotes market-level variables. In terms of right hand side variables, supply will obviously be a function of the market price of good one in location

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the production function, and the latter, as the creation of new production functions. Product innovations reduce the cost of satisfying existing needs. In actuality, the classification of innovations depends on the perspective."

one (P_{11}), a scale and scope indicator for firms in location one (L_1, C_1), the distribution factors for good one in location one ($f_{11}^a, f_{11}^b, f_{11}^c$), and other factors, such as input prices, number of producers, and seasonal factors, all subsumed in the vector $\boldsymbol{O}^S$. The market level supply function for good one in location one then becomes:

$$Q_{11}^S = Q_{11}(\underset{(+)}{P_{11}}, \underset{(+)}{L_1}, \underset{(+)}{C_1}, \underset{(?)}{f_1^a}, \underset{(?)}{f_1^b}, \underset{(?)}{f_1^c}, \underset{(?)}{O^S}):\ \textit{Market One Supply Function} \tag{14}$$

The parenthetical question marks as before indicate that the direction of the relationship between the variable and the quantity supplied could be zero, negative, or positive, depending on the type of distributional service provided or other variable. In terms of the market supply curve, a change in the price P_{11} is captured by a movement along the supply curve and a change in any other variable $(L_1, C_1, f_{11}^a, f_{11}^b, f_{11}^c, \boldsymbol{O}^S)$ will cause a shift in the supply curve with the direction of the shift being determined by the sign under the variable.

5 Graphical Equilibrium Analysis of Some Topical Questions

With both the demand and the supply sides developed, they can be brought together to analyze a few of the questions posed at the beginning of the paper in the typical fashion found in any microeconomics textbook. Before proceeding, the student should be reminded of a few caveats about graphical supply and demand analysis to head off some typical questions. First, there is an art in applying models, and the question dictates the choice. In most undergraduate texts, the questions are often rather general, and therefore, the good is usually some aggregate (e.g., food, food away from home, pizza), and the geographical or temporal aspects of the market may or may not be defined. Second, supply and demand diagrams are qualitative tools, not quantitative tools. They only provide directional insights, not magnitude insights. The size of the shift of a curve could be small or large, depending on the amount the underlying variable changes and the sensitivity of the market to the change. Third, the slopes of the curves could be very flat (very elastic) or very steep (very inelastic), depending on the good, and thus the magnitude of the changes in price and quantity will also depend on these slopes (elasticities). Fourth, in its simplest form, the above analysis relates to demand and supply for a final good (at the consumer level), though the concept of utility is broad enough to include profit, and it could be adapted to any level in the supply chain. Finally, as always, the *ceteris paribus* clause applies, meaning unless stated otherwise, we are conceptually holding all other factors constant, but in reality, multiple factors are usually changing, and the demand and supply curve will shift accordingly.

5.1 Cost Shifting Affecting Demand Only . . . Perhaps

How do device-assisted transactions affect demand and supply? On the demand side, device-assisted transactions lower consumer's search costs, time costs, and cognitive load such that the technology parameters *b* and *c* will be lower or decrease. GPS location–activated searches and sale or price reduction notifications reduce search costs. Voice-activated devices shave off seconds in a myriad of ways, ranging from voice-activated text typing, to thermostat or light settings, to ordering products online. In restaurant markets, apps, such as Trip Advisor, allows one to locate restaurants and see their ranking based on customer reviews, along with pricing information. In the grocery market, there is a dizzying array of apps designing to reduce the cost of all aspects of meal planning, nutrition assessment, and time in the grocery store. These apps integrate several meal production activities in one app, allowing you to search for and save recipes, create shopping lists from recipes, get weekly sales notifications, check for coupons or discounts, comparison item shop, simply scan a bar code of existing items you need to purchase to add to a shopping list, and get an in-store navigation map (Klecker 2019). Thus, on the demand side, device-assisted transactions lower the full price and lead to a higher derived demand for the good.

On the supply side, apps are especially appealing to firms because they exploit a technology standardization, like a public good, that can be leveraged at a relatively low cost to provide greater service (Pantano and Viassone 2014). Customers own and pay for the information delivery device and its operation (the phone and data), they are already familiar with how to use the device, and firms need only provide the resources needed to develop and maintain the app. Depending on the app and its maintenance, this cost *may* affect marginal cost, but for initial simplicity it is assumed to only affect average cost, not marginal cost, and thus leaves the (short run) supply curve unaffected. Figure 1 then shows a graph of the market for the good (e.g., groceries) where there is a demand curve where the device-assisted transactions are not available (D^0) and then a higher demand (D^1) where these services are available and, *ceteris paribus*, more of the good would be sold and for a higher price, but again magnitudes will depend on slope and shift magnitudes. Of course, if these costs of providing these services affected marginal cost, then the supply curve with these services would be higher and the price effect higher and the quantity effect attenuated.

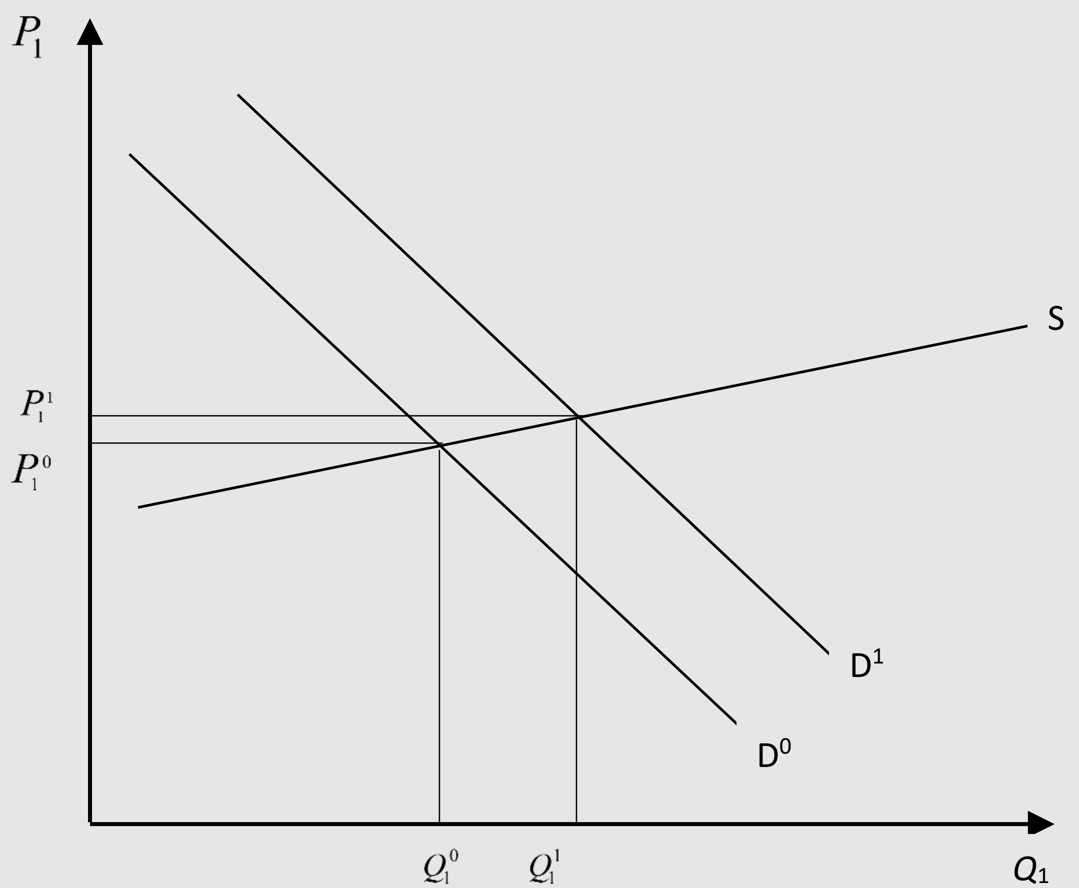

Figure 1. Supply Neutral Cost Shifting Increasing Demand

Application: Transaction-Assisted Devices. Cost shifting that does not affect the short-run supply curve, such as transaction-assisting devices, leading to higher demand ($D^1 > D^0$) because of lower time and effort costs ($b_1 < b_0$, $c_1 < c_0$), and thus lower full price.

How are online, offline grocery shopping, meal kits, and the emergence of grocerants all connected? "The U.S. e-grocery market had a share of 3 percent of total sales in 2016. The market share was expected to grow to 10 percent by 2020" (Statista 2019). However, a recently published article in *The Atlantic* has the title, "Why People Still Don't Buy Groceries Online" (Semuels 2019). The title implies it is a demand side problem. It is actually a supply side problem. Four key product attributes come into play in analyzing the economics of online versus offline purchases: (i) the *quality heterogeneity* of individual products within the order, (ii) the *perishability* of the products within the order, (iii) the *number* of products in the order, and (iv) the packing *arrangement* of the order. Orders where these attributes are not that important are better suited for online purchases and delivery than products where these attributes are important. For example, electronics, household goods, and even clothes are mass-produced with very uniform quality, are not perishable, and can be combined in a single order with little concern for packing arrangement. On the other hand, there is a great deal of possible heterogeneity for a grocery item (e.g., green vs. ripe bananas), many grocery items are highly perishable (e.g., ice cream), the number of possible product combinations from a grocery store can quickly approach infinity, and the packing arrangement of groceries is very important (e.g., bread needs to be placed in the top of the bag). Thus, the more important these attributes are, the costlier it will be to process orders and deliver the orders. Stated succinctly in economic terms, the more important these attributes, the more labor intensive and less capital intensive is the online business model and economies of scale are difficult to achieve, especially in delivery. The basic economics of transportation costs indicate it is much cheaper per trip if a large truck can be sent to a densely populated area to deliver groceries than sending many smaller trucks to widely dispersed customers. What one would expect to see is that online grocery shopping and delivery would be more prevalent and potentially more profitable in densely populated areas, and this is indeed the case. For example, the Amazon Fresh delivery service announced last year it was suspending service in some areas while still providing services in cities such as New York, Chicago, and Boston (Semuels 2019). An intermediate business model that is more cost effective is to scrap the delivery service in markets where that cost is high, but still do a “click and collect” where the customer can shop online and then go to the store and pick up the order that was filled by store employees.

The economics of meal kits are similar. Just a few years ago meal kits were the new rage in the food sector (e.g., Blue Apron, Home Chef, Plated); not anymore. “Few business models are as unprofitable as those of meal-kit companies” (Ladd 2018). Why? On the supply side, the cost of meal kit delivery faces all the logistical hurdles of delivering grocery orders mentioned above, but with the added labor (and capital!) costs associated with designing meals, purchasing ingredients, preparing ingredients, packing meal kits, and marketing their brand. Thus, it is an even more labor-intensive service and thus would demand a much higher price to cover this extra cost. However, on the demand side, there are also economies of scope for the consumer associated with an offline store, meaning the full average price per item purchased can be lower when all items can be purchased in one sitting or location (i.e., one-stop shopping), without having to switch gears, perhaps figuratively and literally, from shopping in one place to go to another to get different products. And furthermore, there is effectively no barrier to entry preventing grocery stores from offering meal kits. Given the economies of scope advantage of grocery stores over meal kit companies, it makes sense to make the meal kit just another category line in the grocery store at a lower price point, and indeed, this is what has happened as many meal-kit businesses have now either signed agreements or been bought by traditional retail outlets (e.g., Albertsons and Plated, Kroger and Home Chef) such that meal kits are now sold in grocery stores.

The economies of scope of cost shifting within the grocery store also help explain the emergence of the sit-down restaurant in the grocery store or the “grocerant” (Meyer 2017). Grocery stores already have in the store ease of access to many of the inputs needed for operating a restaurant area, and thus the additional costs are not that high. Consequently, the restaurant can be thought of as the addition of another category line in the convenience spectrum from basic ingredients, to semi-prepared foods, to meal kits, to ready-to-eat take out, to sit down meals. In fact, one could predict that grocery stores will continue to look for economic opportunities all along the convenience spectrum, perhaps even going in the opposite direction by growing food within the store and letting the individual “pick their own,” as is being explored by Kroger (Browne 2019). Thus, by offering products along the entire convenience spectrum, they are also able to attract *all* the consumers along this spectrum as well.

Figure 2 demonstrates all of these market observations. The 0 superscript could denote the online grocery market conditions with a higher per unit cost and price P^0. The 1 superscript could denote the offline grocery market with lower per unit cost and price P^1 because of scale and scope economies and a

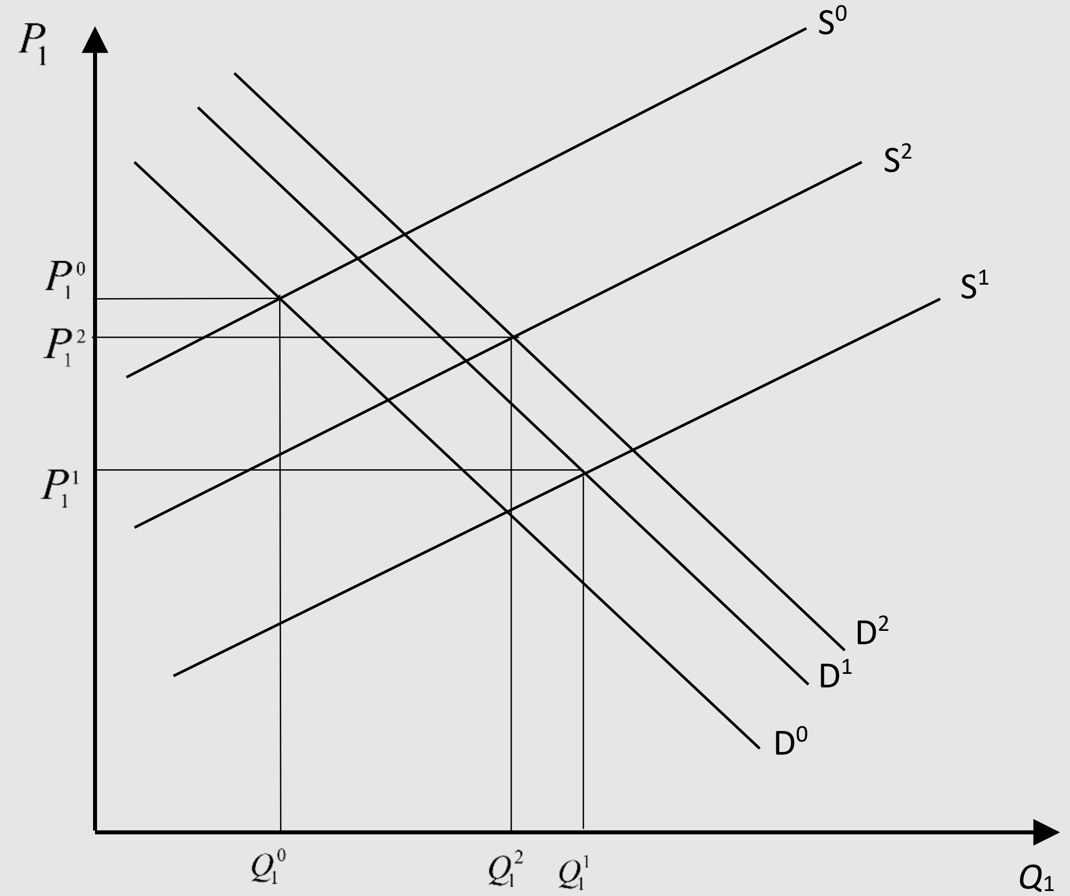

Figure 2. Cost Shifting Affecting Supply and Demand

Applications: Online vs. Offline Groceries, Grocerants. Online grocery markets with delivery are denoted by 0, offline grocery markets are denoted by 1, and grocerant markets are denoted by 2. Online grocery markets with delivery are expected to have higher costs than offline grocery markets such that $S^0 < S^1$ and *perhaps* lower demand because of diseconomies of scale in consumption relative to offline markets ($D^1 > D^0$). Grocerant markets are expected to have higher costs than regular offline grocery because of providing more services ($S^2 < S^1$), but this cost shifting would be expected to lead to higher demand ($D^2 > D^1$). Thus, we would expect to see higher prices and lower quantities for online grocery markets relative to offline grocery markets ($P_1^0 > P_1^1, Q_1^1 > Q_1^0$) and higher prices and lower quantities for grocerant markets relative to offline grocery markets ($P_1^2 > P_1^1, Q_1^1 > Q_1^2$), ceteris paribus. Note the general qualitative conclusion does not change if it is believed online has a higher demand than offline (i.e., switch the two demands).

higher demand resulting mainly from consumer economies of scope (one-stop shopping). The 2 superscript could denote the offline grocerant market, which relative to a grocery market would have higher labor cost (*ceteris paribus*) because of the restaurant component, with a higher price P^2 but also a higher quantity Q^2 than the regular grocery store.

What does convenience have to do with food deserts? Over the last decade, there has been much concern about food deserts, which is defined generally as an area devoid of a supermarket (Walker, Keane, and Burke 2010). Analyses have focused on demand side characteristics of households and compared them between food desert and nonfood desert areas. The most important finding is that food deserts are located in low-income areas or stated conversely, nonfood deserts are located in higher income areas. In addition, one of the supposed puzzles is that food deserts tend to have higher prices than nonfood deserts (Powell et al. 2007; Dutko, Ver Ploeg, and Farrigan 2012). This is only a puzzle if one ignores the economics of the supply side and specifically the store location decision. The economics—demand and supply—of convenience helps explain this observation.

Profit margins in the grocery industry are some of the smallest in any industry (1–3 percent; Forbes 2016), and this is again where economies of scope, scale, and cost shifting intersect as there are built-in incentives to increase the size of grocery stores and services (Ellickson 2016). On the revenue side, though profit margins on a whole for grocery stores are small, products that contain more cost shifting have higher margins, such as ready-to-cook or ready-to-eat items found in the deli or bakery sections (Johnson 2019). The individuals who are willing to pay higher prices for these service-embedded goods are going to be those with higher incomes and higher time costs. Thus grocery firms have incentives to locate where incomes are higher and the opportunity cost of time is higher. The theory then suggests we would expect to see firms locating stores in higher income areas and providing a continuum of services that reduce the full price, ranging from more products in a single location to a wider distribution of the types of products (basic ingredients to the in-store restaurant). Pashigian, Peltzman, and Sun (2003) provide evidence that grocery stores have responded to higher time cost of households by hiring more in-store labor (providing more services, such as the bakery or deli) and locating in places that are more convenient for individuals with a higher time cost. Thus, this is a case where one needs to remember the *ceteris paribus* condition in the graphical analysis, because grocery firms have simultaneously been exploiting scale and scope economies, which would shift out the supply curve, but also providing more labor-intensive services, which would tend to shift the supply curve back. This then helps explain how it is possible to simultaneously observe low-income areas facing higher prices and less services.

Figure 3 demonstrates this case where now the 0 superscript refers to the market in food desert areas with prices and quantities P^0 and Q^0, respectively, as a result of lower values of the scale, scope, and distribution services variables (i.e., L, C, f^b, f^c) . The 1 superscript denotes the market in the nonfood desert area with lower costs because of scale and scope economies but also higher demand because of more services with corresponding lower prices and higher quantities P^1 and Q^1, respectively.[12]

6 Conclusions and Extensions

Convenience is perhaps the most important "commodity" being sold in the market today, and yet there is nothing of analytical substance to be found in most undergraduate textbooks. This article fills this important gap in a straightforward manner by incorporating convenience in the typical supply and demand framework using the standard tools of introductory and intermediate microeconomics. This was achieved on the demand side by using Becker's (1965, 1985) household production theory to include time and effort technology and resource constraints leading to full prices that consist of the direct market price plus indirect time and effort prices. On the supply side, retail supply and distribution theory (Betancourt 2004) allowed for an interaction of scale and scope economies and cost shifting services that led to suppliers providing services that not only affect supply but also demand via the direct effect on the indirect time and effort prices, which in turn affects the direct market prices and quantities as well. The framework was used to answer several questions related to convenience that could not be answered with the standard supply and demand framework that does not explicitly account for convenience.

The framework could be employed in analyzing numerous other questions as well. For example, why are advertisers willing to pay 2.7 times more for behaviorally targeted ads than nontargeted ads, as suggested by one study (Beales 2010)? Or why, according to a report in Forbes, do "70 percent of advertisers currently work with influencers, and 40 percent plan to increase influencer budgets in the

[12] This graph is consistent with what has been found empirically, but it implies that the outward supply shifts are greater than the outward demand shifts. This situation does not have to be the case and would vary by market and good. This is just a case of the more general principle of demand and supply: if supply and demand shift in the same direction, we can only be certain about the direction of the quantity change. Price may increase or decrease depending on the magnitude of the shifts. Alternatively, if supply and demand shift in opposite directions, then we can only be certain about the direction of the price change.

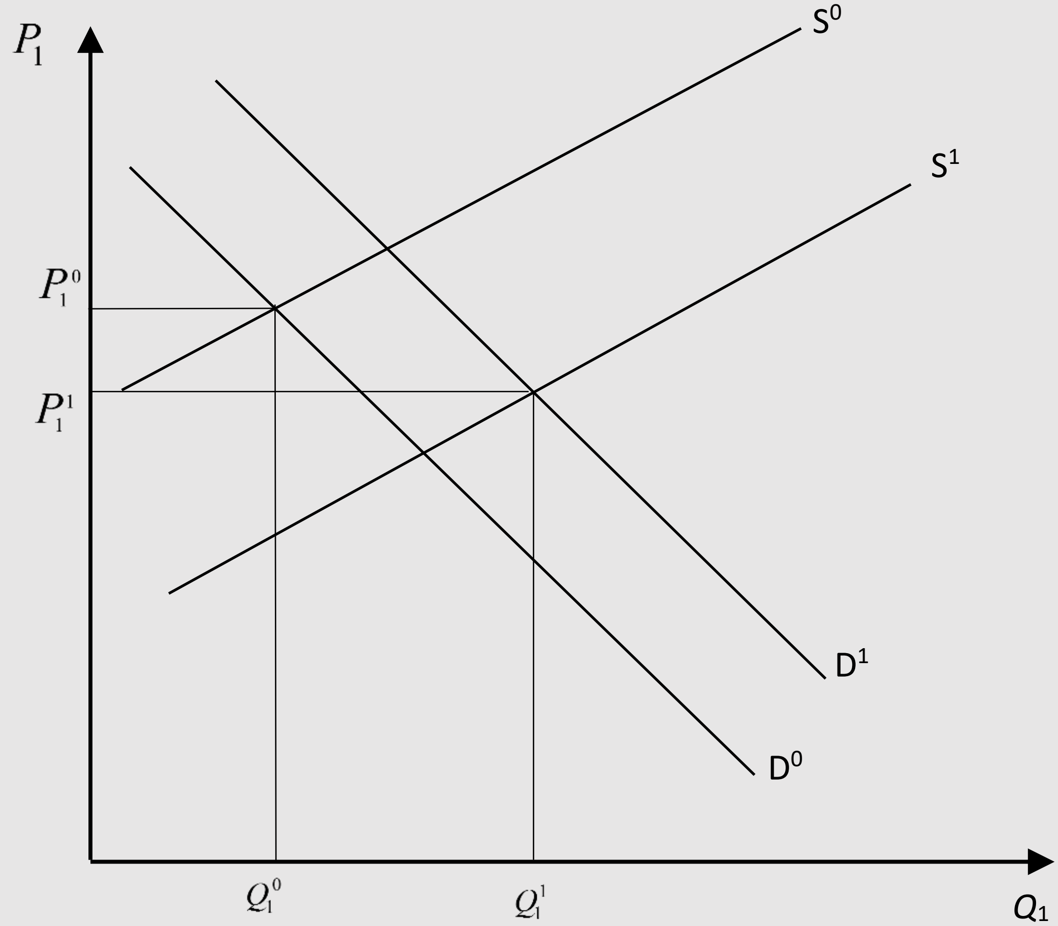

Figure 3. Economies of Scale, Scope, and Cost Shifting Affecting Supply and Demand

Applications: Food Deserts vs. Nonfood Deserts. Food desert grocery markets are denoted by 0 and nonfood desert grocery markets are denoted by 1. Grocery stores in nonfood deserts are expected to be larger, provide a larger variety of products, and provide more services, thus benefit from economies of scale and scope, even with more cost-shifting services, such that $S^0 < S^1$. Nonfood deserts are expected to have higher demand because of more services reducing time and effort cost, but also higher income, so $D^1 > D^0$. Thus, if the economies of scale and scope outweigh the cost-shifting effects, then food deserts will have higher prices and lower quantities than nonfood deserts ($P_1^0 > P_1^1, Q_1^1 > Q_1^0$).

coming months" (Davis 2019)? What is the economic commonality in the development of a faster charging or longer lasting battery for a handheld device or an electric car?

Perfect competition was assumed because that is the entry point for undergraduates being taught market equilibrium analysis for the first time. As alluded to, there certainly may be applications where an imperfectly competitive market model would be more appropriate. The analytics for imperfect competition extensions are rather straightforward (e.g., monopoly, duopoly, monopolistic competition). The key is to capture all the main components within the imperfectly competitive model. On the revenue (demand) side, the key is to work with a derived demand function for the good expressed in terms of full prices, not just market prices. The full prices are functions of the household technology parameters, which in turn would be functions of the firm's distribution services. On the cost (supply) side, the key is to have a cost function that contains scale, scope, and distribution service components. Thus, the firm (or firms) then chooses not only price (or quantity) of the market good but also levels of distribution services and perhaps even scale and scope variables as well. This quickly could get complicated if one wants to consider response functions of other firms. However, none of this would tend to change the fundamental equi-marginal intuition, which is simply that firms are willing to bear some of the burden of shifting time and effort costs from consumers to firms (cost shifting) if the marginal revenue exceeds the marginal cost, and this will have implications for the direct prices and quantities of goods sold in the market.

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