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Navigating the corn maze: Customizing travel cost models to value market segments in heterogeneous industries

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Abstract
Agritourism is an example of a growing and important industry to rural communities in the United States seeking to leverage interest in their natural resource, agricultural, and other heritage assets. We use survey data and a flexible travel cost model to estimate the part-worth consumer surplus (CS) values of Western US agritourism trips for different regions, activities, and traveler types. Given the rural nature of agritourism may require interested travelers to come from long distances, we also pay particular attention to and compare travelers' marginal and cumulative travel costs to evaluate the impact on CS estimates. Results indicate that trip and traveler heterogeneity, if unaccounted for, may lead to misinformed policy and management decisions.

Keywords
agritourism, consumer surplus, demand, multi-destination, rural tourism, travel cost model

Introduction

Tourism is an important and growing industry in many regions of the United States and the broader global economy. Given the strengthening interest in outdoor recreation, as well as local food, beverage, and heritage experiences, rural America is well-positioned to attract economic activity from multiple traveler segments (Carpio et al., 2008; Van Sandt et al., 2018). As an illustration, the

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number of farms with agritourism, a fee-based recreational or educational activity that takes place on a working farm or ranch, grew 48% between 2007 and 2012, yet still only includes roughly 2% of farms and ranches (Van Sandt and Thilmany Mcfadden, 2016). However, the competitive positioning of the predominantly rural agritourism sector will have to be aware of how remote locations and travel distances affect relative demand, and accordingly, what current agritourists' behavior may allow one to infer about current total sector demand. Tourism is an interesting case to explore heterogeneous preferences as traveler demand is likely dependent on a mix of location and trip/experience-based attributes (Santeramo and Barbieri, 2017).

Since its origins in the 1970s, the travel cost method (TCM) is a key method used in estimating consumer surplus (CS), recreation demand, total use values, and in evaluating policies for non-market goods. The primary reasons for the TCM's frequent use are its ability to determine CS estimates using observed market behavior that can be collected through primary or secondary sources and its ability to circumvent biases that arise in stated preference models. A seemingly exhaustive set of topics have been evaluated with TCMs from whale watching (Loomis and Larson, 2000) to the Grand Canyon (Morgan, 1986) and deer hunting (Balkan and Kahn, 1988) to the Great Barrier Reef (Carr and Mendelsohn, 2003) to guide policy and management decisions revolving around resource management, consumer welfare, and economic development. Despite the many applications and methodological refinements of the TCM, multi-destination (MD) bias is one issue that continues to challenge applied researchers who want to provide reliable and disaggregated estimates to industry and policy stakeholders.

The central idea of the TCM is that a consumer's true willingness to pay (WTP) for a specific activity is not only the price explicitly paid to partake in the activity but also the implicit cost of traveling to the site and the opportunity cost of time. However, a key empirical issue arises when a traveler visits multiple destinations on a single trip and the researcher is unable to precisely determine the incremental cost in traveling to each site. In essence, on a MD trip, the travel cost for a particular tourism experience may not be the distance from the traveler's point of origin, but rather the incremental distance traveled from the visitor's primary path of travel to the additional destination. This measurement error in the TCM leads to biased CS estimates: an issue that arises in the vast majority of travel cost studies due to travelers bundling destinations to maximize their utility per dollar (and nonpecuniary time cost of travel). Moreover, the direction and degree of the bias may vary by the context of the sites visited. For the past several decades, the TCM literature has attempted to account for traveler heterogeneity in the modeling stage, but progress has largely stalled. We fill a gap in the literature by using refined survey data that specifically capture MD travel behavior and may be used to empirically identify the MD bias in CS estimates.

The key research question of this article is to explore if and how the bias in CS estimates from MD trips may be reduced with more refined data collection and modeling. Using a more general TCM modeling approach, we present refined values for the diverse agritourism sector of the Western United States which serves as an effective empirical example to differentiate how the inferred demand for place- and experience-based attributes can be better estimated when accounting for MD trips. Rather than focusing on valuing one specific site, the model is used to estimate the CS visitors receive from the broad set of agritourism sites in the Western United States. Agritourism is an ideal industry to use in this analysis due to its large degree of heterogeneity in activities (i.e. wine tours, corn mazes, hunting, etc.), traveler types (MD vs. primary purpose travelers), and place-based (climate, topography, culture, etc.) variability. Results indicate that the MD effect can lead to a significant upward or downward bias in CS estimates, depending on the geographic region and recreation experiences offered. Averaging across regions and activities, the MD bias ranges from +244% for MD visitors to −10% for primary purpose visitors: the magnitude of this bias could severely distort policy and management recommendations.

The possibility for biases in CS estimates from the presence of MD travelers was first fully articulated by Haspel and Johnson (1982), and many studies have noted or attempted to account for MD bias since the genesis of the TCM. Comprehensively correcting for the MD bias will increase the validity of future travel cost models building on previous work focused on other biases that may occur, such as omitting substitute prices or the inclusion of opportunity costs of time (Bockstael et al., 1987; Rosenthal, 1987). Rather than relying on previous methods for handling MD visitors, this article makes use of a rich visitor survey data set with questions specific to comprehensive[1] and incremental travel costs incurred, site attributes, and visitor types meticulously to account for the MD bias. A flexible functional form similar to that used by Parsons and Wilson (1997) and Loomis and Larson (2000) is applied to estimate demand for agritourism across six regions, four activities, and two different traveler types. Four progressively flexible empirical models and a unique zonal hybrid TCM approach are employed to illustrate the importance of accounting for industry heterogeneity and use these flexible models to identify specific trip types where correcting for MD bias may be more important.

After presenting an overview of previous literature's handling of MD biases, this article outlines the survey instrument and the basic microeconomic theory of utility maximization used to develop travelers' Marshallian demand curve. The theoretical implications of not properly measuring MD travel costs are presented along with a discussion of how the empirical model more accurately accounts for heterogeneity, leveraging the results from the flexible form developed in the prior section to illustrate circumstances that signal when future travel cost studies may need to be concerned with MD bias.

Background

Travel cost studies continue to be published frequently on a myriad of topics; however, there are few recent studies that explore the MD bias or other TCM improvements that are relevant here. Thus, much of the literature appears dated despite being the most recent advancements in the TCM. In addition, some of the literature's findings contradict one another, highlighting the need to further explore latent nuances. In this section, we give an overview of the relevant travel cost literature pertaining to the MD bias before expanding on CS estimation and the hypothesized consequences of the MD bias on CS estimates.

Haspel and Johnson (1982) were the first to highlight MD bias in their application of the TCM to Bryce Canyon National Park where they suggested treating the average distance between visitors' destinations as the marginal travel cost to the site for any MD visitors. While an improvement, their proxy is only valid if each of the destinations and the traveler's origin are equally spaced (the three parks considered in their article are each roughly 2 h apart). They find no significant differences between their proposed travel cost model's CS estimates and measures of consumer welfare. However, Bishop and Heberlein (1979) find different consumer welfare results when comparing alternative travel cost specifications to direct measures.

Haspel and Johnson's (1982) evidence that inconsistencies in parameter estimates from the MD bias might vary depending on the nature of the recreational activity is a key contribution to the field. But, there is no clear consensus on how to overcome the issue or consequences from such misspecification. Some proposed methods to account for the MD bias include dropping all MD visitors from the sample (Smith and Kopp, 1980), treating MD trips as bundles of goods

(Mendelsohn et al., 1992), and more recently, using simple econometric specifications to account for shifts and rotations of the demand curve for primary purpose and MD visitors (Hill et al., 2014; Loomis and Larson, 2000; Parsons and Wilson, 1997). While some articles such as Loomis and Larson (2000) have attempted to estimate the bias by comparing CS estimates from multiple specifications, no one has directly estimated the bias in a travel cost model or explored how the bias may change across recreational activities and regions.

Instead of using average travel costs or a complex system of demand equations, Parsons and Wilson (1997) include the total travel costs of all visitor types in one variable and tease out estimates of bias by including an intercept shifter and slope rotator for MD travelers. Since the only extra piece of information needed for estimation is defining primary purpose from MD visitors, the ease of estimation makes it a popular approach. Loomis and Larson (2000) delineate between joint and incidental destination visitors by adding in separate slope and intercept shifters and find that failing to control for MD visitors increases the CS values by 20–70%. Although the magnitudes of CS estimates for different traveler types vary, they find no statistically significant differences but note the differences that do exist among the varying CS may still be policy relevant.

Other articles have offered modifications to the original Parsons and Wilson model, most often testing restrictions and attempting to increase explanatory power. Loomis (2006) and Hill et al. (2014) compare several specifications of travel cost models valuing the Snake River in Wyoming and agritourism in Colorado, respectively. Each of these studies expresses a need for more research in better addressing and empirically evaluating the MD bias.

Consumer surplus

CS is calculated by taking the definite integral of the demand curve, defined between the choke price and the market price. In the travel cost model, the travel cost represents the market price of the activity, while the choke price is assumed to be asymptotic to the price axis and approaches infinity as the quantity of trips falls to zero.

The discrete and nonnegative nature of the data and a significant likelihood ratio test of the dispersion parameter (α) imply that a truncated negative binomial distribution is most appropriate for efficient estimation (Creel and Loomis, 1990; Grogger and Carson, 1991; Martínez-Espiñeira and Amoako-Tuffour, 2008). Due to the close relationship between the Poisson and the negative binomial distributions, the first moment of the negative binomial model is simply λ, and in the present context, it can be interpreted as the expected quantity of trips. For estimation purposes, an exponential parameterization is frequently used to restrict the dependent variable, in this case quantity of trips, to positive values. For these reasons, to derive CS, the integral over the demand curve can be written as:

$$\mathrm{CS} = \int_{P_0}^{P_1} \exp(\beta_0 + \beta_1 TC + \beta_k x_k)dp \tag{1}$$

where TC is a vector of travel costs and x_k are other demand determinants relevant to the site and travelers. Given this set up, the average per trip, per-person CS can be expressed as:

$$\mathrm{CS} = -\frac{1}{\beta_1}. \tag{2}$$

Previous studies have estimated part-worth CS estimates, or CS estimates of different groups or aspects of a trip, such as CS estimates for different traveler types (e.g. Parsons and Wilson, 1997), recreational activities (e.g. Hesseln et al., 2003), and locations (e.g. Layman et al., 1996). These part-worth CS values can be achieved by first interacting the travel cost vector with dummy variables indicating different traveler types, activities, or regions. Taking the integral of equation (1) where the TC is interacted with some other aspect of the trip with coefficient β_2 leads to equation (2) becoming the negative reciprocal of the sum of TC coefficients ($CS = -\frac{1}{\beta_1+\beta_2}$) or two part-worth CS values ($CS_1 = -\frac{1}{\beta_1}$ and $CS_2 = -\frac{1}{\beta_2}$). Note that while the law of demand dictates β_1 and β_2 should be negative, it is possible for some of these part-worth TC coefficients to be positive, indicating a more elastic overall demand curve once summed together.

The MD bias

Traditionally, travel cost measurements are either extracted from secondary data sources where the respondent's home and destination zip codes are known or elicited from survey respondents using a similar beginning- and end-point method. The issue with such measurements is that they do not account for the differences in travel behavior between respondents. While a start-to-finish travel measurement might be justifiable for those travelers who treat the site in question as the primary purpose of their travel, this measurement is incorrect for MD travelers or studies such as this seeking to explore the diversity of travelers in this sector. Lue et al. (1993) describe four types of MD trips: en route pattern, basecamp pattern, regional tour pattern, and trip chaining pattern. Each of these MD trips contains nuanced travel behaviors; however, the underlying challenge for the researcher is determining what incremental travel cost should be associated with the destination of interest.

Lue et al. (1993) classify pleasure trips using the dimensions of number of destinations visited and purpose or benefits sought. To justify trip costs, a single destination trip with a single benefit needs to offer very clear and strong utility/benefits to the traveler. Thus, it is the easiest scenario to assign travel costs. For this article, we want to contribute to the discussion of how to disentangle the "revealed" benefits travelers may see from the multiple destinations that travelers may derive benefits from.

The en route and base camp patterns offered up by Lue et al. (1993) suggest that there is a key destination in mind for the traveler, but with intentions to visit several sites in the area to "compile" a greater set of benefits and utility from the trip. By allowing for agritourism to be a primary purpose of the trip, we intend to capture these travel patterns and assign the benefits from the whole trip to agritourism when explicitly indicated through the survey instrument. Lue et al.'s regional tour and trip chaining patterns are important examples to understand how travelers may see a more "equally weighted" portfolio of sites that drive their trip, so the perceived benefits of each site will be part of the "math" for travelers to decide the time and money they are willing to spend on a trip. For this reason, we prioritized including an option for travelers to "assign" the agritourism site(s) they visited as either a secondary or incidental part of their trip, which would be likely if they were a part of those regional tours or trip chains.

Following that logic, the way we collect data on trip purpose and use that to delineate travel costs is intended to contribute to a needed discussion on how travelers value aspects of their trips. As we explore the economics of agritourism, we can imagine dividing trips into keystone destinations (primary), essential travel nodes (secondary), and impulse stops (incidental) and using that typology to categorize the economic values that travelers place on their trips. So, for keystone

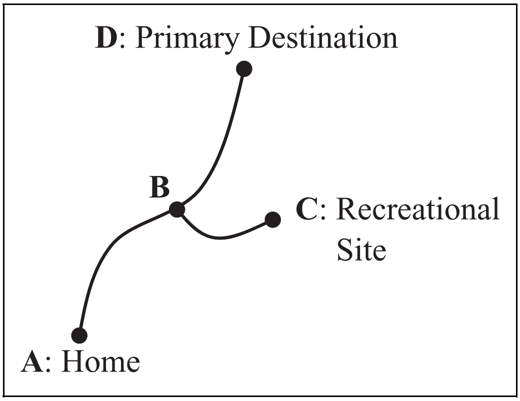

Figure 1. Measuring travel costs for MD visitors. MD: multi-destination.

destinations, any economic activity (measured by travel costs) created by those travelers can be fully credited to those sites. For essential travel nodes and impulse stops, it is important to realize the additional time and monies spent to add the node to a "regional tour" or "chained trip" should be attributed to that site.

Referencing Figure 1, if a traveler's primary destination is not the recreational site, but instead some other destination at *D*, then when considering their travel cost to the recreation area, the first leg of their trip, between *A* and *B*, is a sunk cost. In fact, the only relevant travel cost for these MD visitors is the incremental travel cost from their primary path of travel at *B* to the site in question at *C*. Empirically, this can be thought of as a potential measurement error bias if the travel cost is inflated by some sunk cost (*A* to *B*) for MD travelers, where the individual's travel cost ($\tilde{\mathrm{TC}}_i$) is made up of their true travel cost (TC_i) plus some positive measurement error (u_i) from including the respondent's sunk costs of travel (equation (3)).

$$\tilde{\mathrm{TC}}_i = \mathrm{TC}_i + u_i \tag{3}$$

In a linear regression model using ordinary least squares, this measurement error can cause attenuation bias. However, in the present analysis, there is no closed form for the parameter estimator, and instead, the Newton–Raphson search algorithm is used to find the parameter values that maximize the log-likelihood equation for the truncated negative binomial. Regardless, a heuristics argument that starts with the simplest specification of the travel cost model with just one independent variable (TC_i) and parameter (β_1) implies that the parameter estimate will be biased downward due to overmeasurement in TC_i. That is, for a specific quantity of trips, $\bar{\lambda}_i$, in order for the equality to hold, the travel cost parameter, $\tilde{\beta}_1$, must take on smaller values relative to β_1 to account for the inflated TC variable from the inclusion of sunk costs. In addition, Cameron and Trivedi (2013) point out that if the variance of an independent variable increases due to measurement error without any change in the range of the dependent variable, then the independent variable must produce a smaller effect.

$$\begin{aligned} &\bar{\lambda} = \exp\left(\tilde{\beta}_1 \tilde{\mathrm{TC}}\right) \ \bar{\lambda} = \exp(\beta_1 \mathrm{TC}) \\ &\ln\left(\bar{\lambda}\right) = \tilde{\beta}_1 \tilde{\mathrm{TC}} \ \ln(\lambda) = \beta_1 \mathrm{TC} \\ &\tilde{\beta}_1 < \beta_1. \end{aligned} \tag{4}$$

Comparing this result to the CS calculation shown in equation (2), attenuation bias in the travel cost parameter may lead to overestimating the CS. This potential overestimation due to the inclusion of sunk costs in the travel cost measurement will be tested using Wald tests between individual pairs and groups of TC parameters between the incrementally and cumulatively measured TC parameters. While the bias in the parameter estimates are due to the inclusion of sunk costs, we have a few a priori expectations of empirical sources that may lead to different magnitudes of bias.

1. The share of MD visitors in the sample: If the share of MD visitors to a particular recreational site is relatively small, then CS estimates may not suffer greatly from the attenuation bias.
2. The relative rurality of the recreation site: Assuming most tourists come from urban areas, the more rural a location is, the larger the sunk costs of travel will be for MD agritourists. These larger cumulative travel costs may lead to a larger MD bias in CS estimates for more rural destinations.
3. The relative price of the recreational activity: The more expensive the ticket price is for a recreational activity, the less the passerby will be willing to travel out of their way to visit the site. This relative difference between the sunk cost of travel and the relatively small incremental travel cost to the additional destination may lead to larger magnitudes of bias in the travel cost parameter estimates.

Data and methods

The data for this article were compiled using a survey distributed by Taylor Nelson Sofres in late April, 2015, using pre-recruited panels, to a stratified regional and national sample of travelers, with a focus on agritourists in the Western region.[2] This method of survey collection reduces the potential for sample selection biases that arise from on-site intercept surveys. The survey varied in length depending on whether the respondent was randomly selected to receive one of the four versions. The two survey versions used in this essay were (1) most recent trip involving agritourism and (2) longest trip involving agritourism, totaling 1001 observations. Details on the specific questions in the two versions will be discussed in greater detail below. In general, questions in the survey asked for distances/time traveled, dollars spent, the primary purpose of the trip, number of agritourism trips taken in a year, types of agritourism activities participated in, and other agritourism or general travel-related questions.

To extract respondents' incremental cost of travel, the survey included a graphic (Figure 1) visually depicting the intention behind the incremental travel cost question for MD travelers. In addition to this question, we elicited respondents' home zip code and the zip code of the agritourism destination to calculate the cumulative travel cost, similar to the zonal TCM (Loomis and Walsh, 1997). Given this approach and the individual specific data, this method can be thought of as a hybrid-zonal travel cost model.

While Loomis and Larson (2000) and Parsons and Wilson (1997) have included dummy variables and dummy interaction terms to capture shifts and rotations for the demand curve, the incremental mileage traveled off of the traveler's path is an innovation of this article to disentangle the true travel cost incurred by the traveler. While we do not completely capture the travel behavior nuances described by Lue et al.'s (1993) four MD trip types (to do so would cause the dimensionality of our data to mushroom), our conception of incremental travel costs may still be applied to each of Lue et al.'s trip types. That is, regardless of the trip type, there will always be a nonnegative incremental travel cost off the primary path of travel to visit an additional MD site.

While some variables such as demographics and type of agritourism site were directly solicited, other variables had to be constructed due to obstacles encountered during the data collection stage. Most travel cost studies revolve around one or a several specific sites allowing them to use an individual or zonal travel cost approach (Loomis and Walsh, 1997). However, given the task of valuing an entire regional sector, directly eliciting the respondent's quantity of trips to the particular site they answered the survey questions on was not feasible. We refine the approach of Carpio et al. (2008), who used the TCM to value agritourism experiences in the entire contiguous United States, by not assuming away site and trip heterogeneity and by creating a richer data set to develop a specific quantity of trips variable. Our dependent variable represents the number of trips an individual took to an agritourism site *like* the one they answered the survey questions on (direct sales, event or entertainment, outdoor recreation, or education), while on a trip (day or overnight) *like* the one they answered the survey questions on.[3,4]

To calculate the opportunity costs of travel, we multiplied the midpoint of their income range (see Table 1), by one third the wage rate given previous literature (Carpio et al., 2008). Incremental trip times were explicitly asked for within the survey, and cumulative trip times were calculated assuming an average speed of 55 mph when the primary mode of travel was a motor vehicle (Carpio et al., 2008). Other types of transportation were included in the sample and calculation of these travel costs are detailed in the Supplementary Appendix; however, the vast majority of respondents traveled by motor vehicle (88%). Regardless of travel mode, the incremental travel distances for MD visitors were always assumed to be done by motor vehicle.

About 27% of the sample were classified as MD visitors who treated the agritourism site as either a secondary destination (19%) or an incidental destination (8%). The potential for a large positive bias is possible considering the disparity in mean incremental travel costs between PP and MD visitors (US$24.30 vs. US$1.49). *Entertainment and events* and outdoor recreation were slightly more popular than *direct sales* and *education* activities, but the similar share of respondents who participated in each activity category implies that the survey captured the industry's activity heterogeneity. The Central and Northern Plains regions were aggregated into the Central/Northern Plains region due to low visitation rates to that region, while the Southwest had the highest visitation level, followed by the Mountain and Northern California regions. The nature of these distinct regions inherently captures the different travel behaviors and preferences between long-haul and short-haul road trippers (Park et al., 2019). For example, there are likely to be more long-haul travelers in the Central/Northern Plains regions simply due to the larger distance intervals between agritourism sites compared to Northern California.

The primary approach we take to observe the bias presented by the different travel behavior of MD travelers is by essentially decomposing segments of agritourism visits as a means to estimate part-worth CS estimates. This section first presents the demand theory behind the TCM and concludes by introducing the empirical model to be estimated and a short review of the survey data sample statistics.

The TCM is based in utility maximization. Equation (5) represents an individual's utility maximization problem, where Q is the quantity of agritourism trips taken, $\mathbf{C}$ is the quantity of all other goods and services consumed, $\mathbf{X}$ is a vector of agritourism site characteristics, and $\mathbf{D}$ is a vector of the individual's demographics. The utility function is assumed to be monotonically

Table 1. Survey descriptive statistics.

Observations: 852

Variable	Mean	Standard deviation	Min	Max
Agritourism trips	2.5716	4.5049	1	80
PP travel cost	US$24.3011	54.5607	0.08	769.5876
MD travel cost	US$1.4875	7.4742	0	93.33333
Travel time (minutes)	106.8179	76.0367	0.01	1251.282
PP visitor	0.7336	0.4424	0	1
Secondary purpose visitor	0.1913	0.3936	0	1
Incidental visitor	0.0751	0.2637	0	1
Female	0.5704	0.4953	0	1
Income*	4.1279	2.0702	1	8
Age	37.3416	14.0050	18	84
Agritourism zones (figure A.1)		Percentage of agritourism sites visited		
Mountain		21.13		
Southwest		26.17		
Central		1.64		
Northern Plains		7.87		
Northern California		19.25		
Northwest		12.32		
Greater Texas		11.62		
Agritourism activities		Percentage of agritourism sites visited		
Direct sales		33.80		
Entertainment and events		43.43		
Outdoor recreation		43.19		
Education		32.98		

Note: PP: primary purpose; MD: multi-destination.
*Income has eight categories: 1 = under US$30k, 2 = US$30k–US$40k, 3 = US$40k–US$50k, 4 = US$50k–US$75k, 5 = US$75k–US$100k, 6 = US$100k–US$125k, 7 = US$125k–US$150k, 8 = US$150k and over.

increasing and is constrained by their income (M), the travel cost associated with the site (p), and the prices of all other goods and services ($\mathbf{r}$).

$$\text{Max}_{Q,C}\ U(Q,\mathbf{C}|\mathbf{X},\mathbf{D})\ s.t.\ pQ+\mathbf{rC}\ \leq M. \tag{5}$$

Solving this maximization problem across individuals results in the uncompensated demand for agritourism to be empirically estimated:

$$\mathbf{Q}=f(\mathbf{M},\boldsymbol{\gamma},\boldsymbol{\theta},\mathbf{p},\boldsymbol{\varepsilon}), \tag{6}$$

where $\mathbf{Q}$ is an $n\times 1$ vector of the quantity of agritourism trips taken by n individuals, $\mathbf{M}$ is an $n\times 1$ vector of individuals' incomes, $\boldsymbol{\gamma}$ is an $n\times k_1$ matrix where k_1 are demographic variables, $\boldsymbol{\theta}$ is an $n\times k_2$ matrix of site characteristics where k_2 are site descriptors, $\mathbf{p}$ is a vector of travel costs, and $\boldsymbol{\varepsilon}$ is a random error term. According to Rosenthal (1987) admonition to include substitute prices, we adopt Benson et al.'s (2013) approach using the respondents' meal, shopping, and lodging expenditures from the agritourism site's surrounding area as a proxy for substitute prices.

Accounting for industry heterogeneity

Agritourism is an ideal sector to explore and understand how the MD bias can affect CS estimates across traveler types, activities, and regions.[5] Firstly, agritourism has a high degree of different traveler types. In a TCM for agritourism in Colorado, Hill et al. (2014) find over two-thirds of agritourists were MD travelers (i.e. visited the site as a secondary or incidental stop).

Agritourism experiences also differ in the types of activities offered. While previous travel cost studies on agritourism do not account for heterogeneity in terms of activity participation (Carpio et al., 2008; Hill et al., 2014), we hypothesize the value aligned with these activity categories will influence travel costs differently within the context of agritourism. Tew and Barbieri (2012) found the most common types of agritourism activities offered by Missouri farms are educational/leisure tours (50%/48%), U-pick (37.7%), and observation of agricultural processes, but given our focus on 12 natural amenity-rich Western states, we assume outdoor recreation will also be a popular set of activities. We categorize agritourism activities as either being on-farm direct sales (e.g. U-pick produce, farm store, Christmas trees, etc.), entertainment and events (e.g. farm dinners, concerts, wine tours, etc.), outdoor recreation (e.g. hunting, horseback riding, birding, etc.), and educational activities (e.g. work experience, artisan food demonstrations, historical excursions, etc.).

The CS of a visitor's agritourism experience is likely to differ across regions. For example, a consumer is likely to place a different value on a wine tour experience in Napa Valley, CA, than on a similar experience in Wyoming. In addition, Carpio et al. (2008) find that region of residence matters: respondents living in rural areas make 4.2 times as many agritourism trips than their urban counterparts. To capture differences in Agritourists' CS values across regions, we defined seven agritourism zones across the Western United States.[6] The extents of these regions were delineated through a principal components analysis on county-level characteristics.[7] Using agritourism scores, a choropleth map was created to group counties together based on similar scores.[8] In addition, since this chapter attempts to explore differences in CS across space and agritourism activities, we sought to create regional zones that represented similar characteristics of agritourism, rather than simply using administrative geographical units.[9] The seven agritourism zones were labeled as follows: Northwest, Northern California, Southwest, Central, Northern Plains, Mountain, and the Southern Plains.

Empirical model

To observe the consequences of restrictive travel cost model specifications, we developed four model specifications, each less restrictive than the one before based on a priori expectations set by the literature. Although much of the literature has revolved around MD travelers, it is not clear as to whether the traveler heterogeneity included in model 3 will be statistically superior to the regional and activity flexibility in model 2. Likelihood ratio tests for model fit will be used to test the explanatory power of each specification.

1. The first model represents a standard TCM with no delineation between traveler type, region, or agritourism activities.
2. Model 2 accounts for greater regional and agritourism activity heterogeneity by interacting TCs with regions and activities but omits traveler types.
3. Model 3 is the opposite of model 2 and closely resembles the Parsons and Wilson method by incorporating traveler heterogeneity, but not regional or agritourism activity types.

Table 2. Travel cost models of varying degrees of flexibility.

Variables	Model 1 Standard TCM	Model 2 TC interactions	Model 3 Parsons and Wilson	Model 4 Fully flexible form
Travel cost	X	X	X	X
TC × activities		X		X
TC × regions		X		X
TC × MD			X	X
Flexibility	None	Experience	Traveler	Full
Wald χ^2	90.36***	113.38***	95.69***	149.76***
Pseudo LL	−1353.94	−1337.68	−1353.00	−1329.03

Note: TCM: travel cost method; MD: multi-destination; LL: log likelihood. Each model was estimated using incremental TC calculations.
***Model is significant at the 1% level.

4. Model 4 offers the greatest flexibility in terms of intercept shifts and slope rotations across the three sources of heterogeneity: agritourism activity, region, and traveler type.

The empirical specification employed for model 4 is presented in equation (7), and the reader can deduce the specifications of models 1–3 from this equation and Table 2. In model 4 (equation (7)), traveler types were interacted with both regions and activities; however, perfect multicollinearity is avoided, since activities offered at the site are not mutually exclusive. Note the constant is suppressed making the reference group primary purpose travelers participating in some activity or set of activities; a choice made due to a relatively flat likelihood function that caused issues with convergence in the iterative maximum likelihood estimation process. By suppressing the constant, the variability in the data is effectively forced to be captured by the variable coefficients rather than being absorbed by the constant.

The fully flexible form utilized in model 4 can be written as:

$$\begin{aligned} \boldsymbol{Q}(\textbf{trips}) = {} & \boldsymbol{\beta}_1(\textbf{TT} \times \textbf{PP}) + \boldsymbol{\beta}_2(\textbf{TT} \times \textbf{MD}) + \boldsymbol{\beta}_3\ \textbf{secondary} + \boldsymbol{\beta}_4\ \textbf{incidental} \\ & + \boldsymbol{\beta}_5\ \textbf{inc} + \boldsymbol{\beta}_{k1}\ \textbf{activities} + \boldsymbol{\beta}_{k2}\ \textbf{activities} \times (\textbf{PP} \times \boldsymbol{TC}) \\ & + \boldsymbol{\beta}_{k3}\ \textbf{activities} \times (\textbf{MD} \times \boldsymbol{TC}) + \boldsymbol{\beta}_{k4}\ \textbf{regions} \times (\textbf{PP} \times \boldsymbol{TC}) \\ & + \boldsymbol{\beta}_{k5}\ \textbf{regions} \times (\textbf{MD} \times \boldsymbol{TC}) + \boldsymbol{\beta}_{k6}\bar{\boldsymbol{D}} + \boldsymbol{\varepsilon} \end{aligned}, \qquad (7)$$

where TT represents the agritourist's travel time; PP designates a primary purpose traveler; MD designates a MD traveler; secondary is a binary variable taking a one when the agritourism visit was planned but not the primary purpose; incidental is a binary variable taking a one when the agritourism visit was not planned; inc represents the agritourist's income; activities are dummy variables indicating the agritourism activities participated in; regions are dummy variables indicating the agritourism region the respondent visited; ***TC*** is either the cumulative or incremental travel costs; $\bar{\mathbf{D}}$ represents trip and traveler specific characteristics such as surrounding area expenditures, age, whether the respondent engaged in multiple activities, and the natural amenities index for the county the agritourist visited; and ε is a random error term picking up unobserved factors.

This fully flexible form in equation (7) allows for different demand curve intercepts across traveler types (β_3 and β_4) and activities (β_{k1}), as well as rotations in the demand curve for each activity (β_{k2} and β_{k3}) and region (β_{k4} and β_{k5}) across traveler types. Each of the preceding three models is special cases of equation (7), and although the constant is suppressed, equation (7) theoretically collapses into the other three models if none of the coefficients within k_4 and k_5 and k_2 and k_3 are significantly different from one another.

Results

All models were estimated using a constant-suppressed truncated negative binomial via maximum likelihood estimation. While heteroscedasticity was not tested for, each model made use of White's robust standard errors to improve efficiency without affecting the consistency of parameter estimates. Each model was tested for multicollinearity using an un-centered variance inflation factor (VIF). The average VIF for the model was 2.96, well below conventional multicollinearity thresholds. Significant levels of multicollinearity were detected in model 4 for two MD travel cost interaction variables,[10] but due to significance across the variables of interest, it does not appear to negatively affect the consistency or interpretation of results.

Table 2 presents the four model specifications with varying degrees of flexibility in their treatment of activities, regions, and travelers. Using likelihood ratio tests for model fit, models 2–4 were all statistically significant improvements on model 1 at the one percent level. Based on the likelihood ratio tests, model 4 also offers a better fit than model 3 at the 1 percent level but is not a significant improvement on model 2. The Wald Chi statistics and pseudo-log-likelihood values listed in Table 2 also indicate an improved fit for models 2–4. However, it should be noted that the travel cost interaction variables' coefficients on two activities (entertainment and events and outdoor recreation) and four regions (Southwest, Mountain, Central/Northern Plains, and Southern Plains) were significantly different between PP and MD travelers.[11] This indicates that including heterogeneity beyond trip purpose accounts for a greater degree of variation in the dependent variable.

The effect of the measurement error can be observed through three different lenses: (1) the effect on the estimated travel cost coefficients, (2) the effect on part worth CS estimates, and (3) the effect on the overall valuation of agritourism in the Western United States. Each of these will be discussed in turn before discussing the industry and policy implications of the varying CS values across regions, travelers, and activities.

Table 3 presentes the results for the fully flexible form of the travel cost equation. Wald tests were conducted on individual travel cost interaction terms, as well as on groups of interaction terms. As a group, the regional travel cost interaction parameters for MD travelers were significantly different when measured with and without measurement error ($p = 0.0225$); however, the primary purpose regional travel cost interaction parameters did not differ significantly. Similarly, the activity travel cost interaction parameters for MD travelers were significantly different ($p = 0.0229$), but the corresponding interaction terms' parameters for PP travelers were not significantly different. This is to be expected considering the measurement error from including the sunk costs of travel only pertains to the MD travelers.

Taking a closer look at these regional and activity interaction terms for the MD travelers shows varying effects of the bias. Employing the Wald test, there were significant differences in the parameters for events and entertainment, outdoor recreation, Southwest, Mountain, and Southern Plains after accounting for measurement error. This indicates that the sunk costs of travel, and therefore, the consumer's travel behavior, differs significantly across activities and regions.

Table 3. Travel cost model 4—Constant suppressed truncated negative binomial.

Variable	Coefficient	Robust standard errors
Travel time—Prim	0.0015**	0.0006
Travel time—MD	0.0054	0.0056
Secondary	−0.3920*	0.2330
Incidental	−0.2670	0.2750
Ln(income)	−0.5550***	0.1570
Agritourism expenditures	−0.0006*	0.0003
Activity types		
Direct sales	−0.0122	0.1870
Entertainment/events	−0.6820***	0.2420
Outdoor recreation	0.3800	0.2450
Education	−0.1820	0.2030
Multiple activities	0.9160***	0.2900
Prim TC × direct sales	0.0026	0.0023
Prim TC × entertainment/events	0.0092***	0.0031
Prim TC × outdoor recreation	−0.0030	0.0023
Prim TC × education	0.0030	0.0030
MD TC × direct sales	0.0524*	0.0307
MD TC × entertainment/events	0.0698***	0.0242
MD TC × outdoor recreation	0.0484**	0.0207
MD TC × education	−0.0013	0.0334
Regional zones		
Prim TC × Mountain	−0.0041	0.0034
Prim TC × Southwest	−0.0045*	0.0025
Prim TC × Central and NE	0.0057	0.0080
Prim TC × Northern CA	−0.0100**	0.0044
Prim TC × Northwest	−0.0054	0.0073
Prim TC × Texas	−0.0056	0.0036
MD TC × Mountain	−0.0736*	0.0396
MD TC × Southwest	−0.1000**	0.0488
MD TC × Central and NE	−0.1870*	0.0994
MD TC × Northern CA	0.0430	0.0832
MD TC × Northwest	−0.0662	0.0482
MD TC × Texas	−0.1200***	0.0441

Note: NE: Northwest; CA: California; MD: multi-destination. Dispersion parameter (α): 1.43***. Observations: 852. Wald Chi: 149.76***.
*Significant at 1% level; **significant at 5% level; ***significant at 10% level.

CS biases

Tables 4 and 5 present the part-worth CS estimates for each activity and region for primary purpose and MD travelers, respectively. Note these are part-worth CS values since each agritourism experience may include more than one activity. The standard deviations for the CS estimates were calculated using Monte Carlo simulations with 500 iterations to develop confidence intervals around the part-worth CS estimates presented in Tables 4 and 5, following Adamowicz et al. (1989). Superscripts denote significance (at the 5 percent level) between CS estimates for other

Table 4. Primary purpose visitors' per-person partial consumer surplus estimates.

	Mountain[1]	Southwest[2]	Central and Northern Plains[3]	Northern California[4]	Northwest[5]	Southern Plains[6]
DTC[A]	US$657.89[ALL]	US$518.13[ALL]	–US$121.21	US$135.69[ALL]	US$362.32[ALL]	US$338.98[ALL]
Standard deviation	4.980704	2.194955	1.052026	0.308093	6.091764	0.900318
Entertainment and events[B]	–US$196.85	–US$214.13	–US$67.34	US$1,298.7[ALL]	–US$260.42	–US$273.97
Standard deviation	0.61573	0.529253	0.322723	9.276213	3.678631	1.928271
Outdoor recreation[C]	US$140.65[ALL]	US$132.98[ALL]	–US$375.94	US$77.16[ALL]	US$119.76[ALL]	US$117.10[ALL]
Standard deviation	0.227238	0.131972	12.73976	0.10614	0.650379	0.142181
Education[D]	US$917.43[ALL]	US$666.67[ALL]	–US$115.21	US$144.09[ALL]	US$429.18[ALL]	US$396.83[ALL]
Standard deviation	10.75081	4.752308	0.941027	0.373352	8.699483	1.378283

Note: CS: consumer surplus; DTC: direct to consumer sales. Superscripts indicate the significance of the CS estimate from other activities (A, B, C, D) and other regions (1, 2, 3, 4, 5, 6).

Table 5. Multi-destination visitors' per-person partial consumer surplus estimates.

	Mountain[1]	Southwest[2]	Central and Northern Plains[3]	Northern California[4]	Northwest[5]	Southern Plains[6]
DTC[A]	US$47.17[2,3,6,C]	US$21.01[1,3,5,6,B,D]	US$7.43[1,2,5,6,D]	–US$10.48	US$72.46[2,3,6,D]	US$14.79[1,2,3,5,B,D]
Standard deviation	5.905498	0.40997	1.197091	4.906431	0.789432	0.376891
Entertainment and events[B]	US$263.16	US$33.11[3,6,A,C,D]	US$8.53[2,6,D]	–US$8.87	–US$277.78	US$19.92[2,3,A,C,D]
Standard deviation	2.383188	0.338322	1.863261	25.1675	0.538602	0.502403
Outdoor recreation[C]	US$39.68[2,3,6,D]	US$19.38[1,3,5,6,B,D]	US$7.22[1,2,5,6,D]	–US$10.94	US$56.18[2,3,6,D]	US$13.97[1,2,3,5,B,D]
Standard deviation	44.15173	1.041223	0.585101	0.967293	3.839151	0.232386
Education[D]	US$13.35[2,3,6,A,C]	US$9.87[ALL]	US$5.31[ALL]	–US$23.98	US$14.82[2,3,6,A,C]	US$8.24[ALL]
Standard deviation	7.331792	1.586491	0.468797	0.678145	10.9298	0.197574

Note: CS: consumer surplus; DTC: direct to consumer sales. Superscripts indicate the significance of the CS estimate from other activities (A, B, C, D) and other regions (1, 2, 3, 4, 5, 6).

estimates in the same column and/or row to facilitate comparisons. All primary purpose partial and MD partial CS estimates, except for MD travelers participating in events and entertainment in the Mountain region, are significantly different from zero. Nearly all of the primary purpose and MD part-worth CS values estimated using the incremental travel costs were significantly different from those estimated using cumulative travel costs.[12]

These CS estimates are part-worth values, so it is not surprising some are negative as they are relative to another region's competitive advantage in attracting visitors for types of activities. For example, Northern California has the only positive primary purpose CS value for entertainment and events most likely due to the region's notable visibility and reputation for winery tastings, events, and tours. Moreover, Northern California's events and entertainment generate the highest CS, indicating primary purpose travelers see all other regions as less desirable event destinations. The negative MD partial CS values for Northern California provide further evidence of this inference.

Table 6 presents the relative bias generated by incorrectly measuring the MD travel costs in model 4. The percent bias is calculated as the percentage change between the CS estimates measured with and without the sunk costs of travel incorporated and, thus, can be interpreted as a relative degree of bias in each partial CS estimate if travel costs are not carefully delineated. As expected, the primary purpose part-worth CS estimates are somewhat biased, but the relative differences are not nearly as large as the biases in the MD partial CS estimates. On average, the primary purpose part-worth CS estimates are depressed by about 10%, whereas the MD partial CS estimates are inflated by 244%. While some MD biases are negative, the majority of the estimates grossly overestimate the values consumers place on the agritourism site, when in reality, travelers would not have traveled such distances for access to only that agritourism activity. Possible reasons for any negative biases in the MD partial CS estimates in Table 6 could be based on (1) different travel behaviors across regions, (2) heterogeneity not yet captured in the data/model, and/or (3) inconsistencies in model 4 parameter estimates from TC measurement error.

Implications for agritourism stakeholders

Analyzing the varying degrees of MD bias across regions and activities leads us to three broad findings that future travel cost studies might use to identify whether the MD bias might be an issue for their study. It is likely that the nature of tourism economics will only become more complex as modes of transportation, resources to plan travel independently, and global incomes rise, all potentially leading travelers to choose to add multiple experiences and sites to their travel excursions. Beyond our contributions to the literature and future research on TCM, these results also have useful implications for the those trying to understand and guide agritourism sector developments in the Western United States (and regions with similar travel activity).

First, the relative price to participate in the recreational activity may affect the magnitude of the MD bias. As one example, trips including the entertainment and events category of activities, which includes wine tours, are overestimated by 3418% in Northern California while education is more modestly overestimated by 302% in the same region. This may indicate that if a recreational site or region is effectively capturing the value of activities using business strategies, then MD travelers may only deviate from their path if the incremental travel cost is significantly low. In other words, relatively expensive agritourism activities are likely to exhibit larger biases in CS if MD status is not accounted for in market analysis, ceteris paribus. For those regions seeking to

Table 6. Relative bias in primary purpose per-person consumer surplus estimates.

	Mountain (%)	Southwest (%)	Central and Northern Plains (%)	Northern California (%)	Northwest (%)	Southern Plains (%)	Average (%)
Primary purpose visitors							
DTC	−10	−6	3	−12	−6	−26	−10
Entertainment and events	1	2	3	−51	1	−28	−12
Outdoor recreation	−9	−8	−10	−11	−8	−15	−10
Education	−10	−4	4	−12	−6	−28	−9
Average	−7	−4	0	−21	−5	−24	−10
Multi-destination visitors							
DTC	−403	−278	538	1355	−177	96	188
Entertainment and events	−134	−198	593	3418	84	66	638
Outdoor recreation	881	−401	352	633	−313	63	202
Education	1128	−844	451	302	−1497	155	−51
Average	368	−430	484	1427	−476	95	244

Note: DTC: direct to consumer sales.

develop and strengthen their agritourism sector, it may be possible to become more competitive if the relative costs of participating offset the additional time needed to get to a more distant location. Continuing with the wine event example, several other Western states have developed their own “wine country” promotions to capture those travelers unable to afford the costs (or latent costs of travel) to that preferred Northern California region.

Second, CS estimates for recreational experiences in more rural areas are likely to suffer more from MD bias. The Central/Northern Plains region exhibits significant bias in MD CS estimates with an average bias of 484% across activities.[13] The large distances between points of attraction, urban or natural, suggest MD travelers participating in agritourism in this region may need to travel relatively farther distances from their point of origin to their destination, developing larger sunk costs, and thereby leading to a larger disparity between the incremental and cumulative travel cost. Consequently, travel cost studies on recreation sites in more rural areas with larger travel distances are likely to suffer significantly more from not addressing the MD bias than those in more populated areas, ceteris paribus. For those seeking opportunities to develop agritourism in isolated, rural areas, these findings may signal the need to “bundle” destinations, so that the perceived marginal travel cost attributed to any one site does not have to bear the full “burden” of the long travel times to arrive in the region. For example, the Four Corners region of Utah, Arizona, New Mexico, and Colorado is an example of a relatively isolated region that has worked together to market their region as a portfolio of recreational choices that make the travel to the region worth the trip (with the help of several long-term and new national parks and monuments).

Finally, the most obvious factor that could influence the magnitude of the MD bias in CS estimates is the share of visitors who are secondary or incidental visitors. CS estimates for a site that is mostly a primary destination may be less likely to be affected by the MD bias. However, given the significant share of MD visitors in the agritourism industry (Hill et al., 2014), the MD bias has the potential to skew the total CS estimate, perhaps in an unexpected direction. This is an important consideration, given a large share of agritourism operations leverage their proximity to other Western travel infrastructure (national parks, key transportation corridors), and they benefit from not having to independently create enough traveler interest to attract customers.

To calculate the total CS for agritourism in the Western United States, each part-worth CS estimate was first weighted by the share of the activity in the region and then multiplied by the share of MD and PP travelers in the region. These weighted CS estimates were then multiplied by 8% (the survey incidence rate) of each county's 18 years and older population for each region and aggregated across regions. When correcting for the MD bias, the total CS was estimated to be US$613.9 million; however, the total CS actually falls to US$466.9 million when the MD correction is not made. This implies an unexpected −24% (−US$250.6 million) from failing to ignore the sunk costs of travel when valuing the region's agritourism sector.

This counterintuitive negative bias is driven by (1) the relative magnitudes of the PP and MD CS, (2) the shares of MD visitors in each region and activity, and (3) the popularity of each activity in a given region. If a region has a small share of MD visitors, even a large positive MD bias will be muted and possibly overcome by a relatively smaller negative bias in the generally larger primary purpose CS estimates. Similarly, some activities have very large positive MD biases, but if that activity is a small share of all activities in the region, then this bias will have little effect on the region's total CS estimate. In short, the varying degrees of biases in CS estimates and the overall downward bias in total CS imply a researcher cannot safely assume a positive or negative MD bias without considering a broader set of factors.

In short, we theorize inaccurate WTP measures are most problematic for tourist attractions with aggressive marketing strategies that extract a significant share of the visitors' WTP, as well as rural tourism businesses or those with high shares of MD tourists due to their location or activity type. This caveat is based on the relative MD biases of TCM estimated CS values for activity types, agritourism regions, and the inherent complexities of MD travelers. For example, an agritourism site offering overnight ranch stays near a metro area should have less concern over the accuracy of WTP estimates based on cumulative TC measures than an agritourism site offering direct to consumer sales in a more rural location. This is partly because MD travelers in urban-proximate areas are more likely to have smaller cumulative TCs (lowering the relative MD bias) than travelers visiting rural destinations.

Conclusions

The TCM is one of the most common options among nonmarket valuation techniques and has been used to influence policy decisions and, in this case, may also inform economic development strategies that incorporate tourism. Yet, the MD bias has posed a significant challenge to the field since the 1980s because it was hypothesized that the bias could grossly overestimate the value of a site or activity and lead to suboptimal policy decisions. The unique flexible form developed here accounts for traveler, region, and activity heterogeneity and can be utilized to measure the MD bias (resulting in more consistent policy analysis).

Empirical results across part-worth CS estimates show that, on average, CS estimates for MD travelers are inflated by 244%, while PP CS estimates are underestimated by 10% when estimated without accounting for incremental travel costs. After exploring relationships between partial CS estimates, the counterintuitive result of the negative bias in the total consumer benefit of agritourism in the West highlights the importance of accounting for consumer, site, and regional heterogeneity in travel cost studies that value more than one site.

In addition to the methodological contributions made to the literature in terms of capturing site, traveler, and regional heterogeneity and the treatment of MD travelers, the empirical findings are relevant to policy makers and industry stakeholders. For example, part-worth estimates are presented as an example of information used to better guide agritourism operators on pricing and broader management strategies (Van Sandt et al., 2020).

Due to the cost of primary data collection, the majority of travel cost studies are estimated using secondary data and zonal approaches. Therefore, future research should explore using the incremental travel cost approach to develop upper and lower bounds for CS estimates when the study is unable to accurately measure and/or comprehensively account for bias. One suggestion for researchers who may not have information on incremental travel costs would be to estimate PP and MD visitors separately to protect the PP estimates from spillover biases from the measurement error in the MD visitors. This segregation may require a larger sample, but at least the researcher can be more confident in assuming an upward bias in the total CS of the recreation experience and can use heuristics based on the relative cost and rurality of the experience to understand the limits of their CS estimates.

Additionally, this article only calculates the bias using one model—a derivate of the Parsons and Wilson model. Other modeling approaches, such as the system of demand equations for bundled destinations by Mendelsohn et al. (1992), should be compared to the incremental TCM to identify if one method of correction provides better estimates over others; specifically, a method that does not require primary data. Finally, there are likely other aspects of consumer behavior that affect the direction and magnitude of the MD bias and exploring these facets may assist researchers in interpreting future and past travel cost models. Considering the large role the TCM plays in recreational, rural development, and resource management policy decisions, expanding the incremental TC literature in these directions will increase the validity of the TCM as a tool for calculating consumer welfare and identifying socially efficient outcomes.

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Notes

1. From hence forth, “comprehensive travel costs” is defined as the travel cost calculated from a traveler’s residence of origin to the recreational activity in question.
2. The initial goal was to survey 1600 travelers who specifically visited agritourism sites in the Western region (Texas, Colorado, Wyoming, Montana, and all states westward); however, Taylor Nelson Sofres’s (TNS) initial screening showed too low an incidence of the participation in the Western agritourism

among travelers in the panel (around 8% instead of the expected 10%) to meet the sample goal. Given this lower than expected incidence, TNS had to both extend their potential sample by using their panel partners to achieve the desired quota of agritourists in the West and make part of the sample based on national travelers who did not visit agritourism sites; hence, there were two additional versions of the survey created that are not used or discussed in the research presented in this article.

3. Several other variables, such as annual number of trips and hours traveled, were cross-checked to ensure the number of trips were consistent with the rest of the respondent's answers.
4. While we do lack specifics on the region(s) of other agritourism trips, overall, we believe this to be a more precise method.
5. As a reminder, agritourism is defined by the literature and United States Department of Agriculture Census of Agriculture as any revenue generating recreational or educational activity paid for by the consumers on a working farm or ranch. Examples include U-pick produce, concerts, fishing, farm dinners, and a variety of other activities.
6. Western States included Washington, Oregon, California, Idaho, Nevada, Arizona, New Mexico, Utah, Colorado, Wyoming, Montana, and Texas.
7. A complete list of variables in the principal component analysis with their associated factor loadings can be found in the Supplementary Appendix. Factor one had the highest Eigen value (1.2769) and factor loadings that aligned with previous work on agritourism in the region (Hill et al., 2014; Van Sandt et al., 2018).
8. From a practicality standpoint, there need to be few enough zones to ensure there are enough degrees of freedom to achieve statistical significance in the multivariate regression analysis.
9. The methods for designing these agritourism zones is presented in the Supplementary Appendix.
10. Variance inflation factors (VIFs) for model 4: MDTC × Mountain VIF = 13.38, MDTC × entertainment and events VIF = 8.79.
11. p Values for noted Wald tests: entertainment and events ($p = 0.0108$), outdoor recreation ($p = 0.0134$), Southwest ($p = 0.0480$), Mountain ($p = 0.0759$), Central/Northern Plains ($p = 0.0548$), and Southern Plains ($p = 0.0086$).
12. Partial consumer's surplus estimates for primary purpose travelers that were not significantly different in model 4 across TC measurements were direct to consumer sales (DTC) and outdoor recreation for the Central/Northern Plains region; DTC, entertainment and events (Ent. & Events), and education (Edu.) for the Northwest region. Multi-destination travelers' partial consumer's surplus for Ent. & Events in the Northwest region was not significantly different across incremental and cumulative TC measurements in model 4.
13. Recall that the motivation to aggregate these two large regions was due to a lack of observations, which can be viewed as a reflection of the low population density (and travel draw) of the aggregated region.

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Anders Van Sandt is an assistant professor and extension specialist at the University of Wyoming. He received his PhD in Agricultural and Resource Economics in 2018 from Colorado State University where he completed his dissertation, *Regional Dimensions of Agritourism: Exploring Spatial and Traveler Heterogeneity*. After graduation, he spent 2 years as a postdoctoral extension associate in the Department of Agricultural Economics at Texas A&M University. He remains dedicated to working with microdata to explore and understand regional economic development issues across multiple sectors in the United States, particularly in rural communities.

Dawn Thilmany McFadden is a professor of Agribusiness and Agribusiness Extension Economist with Colorado State University and specializes in analyzing markets and consumer behavior surrounding local, organic, and other value-added food market segments. She has worked in support of Colorado agritourism development and industry-based efforts (Colorado Wine Industry Development board) since 2005.