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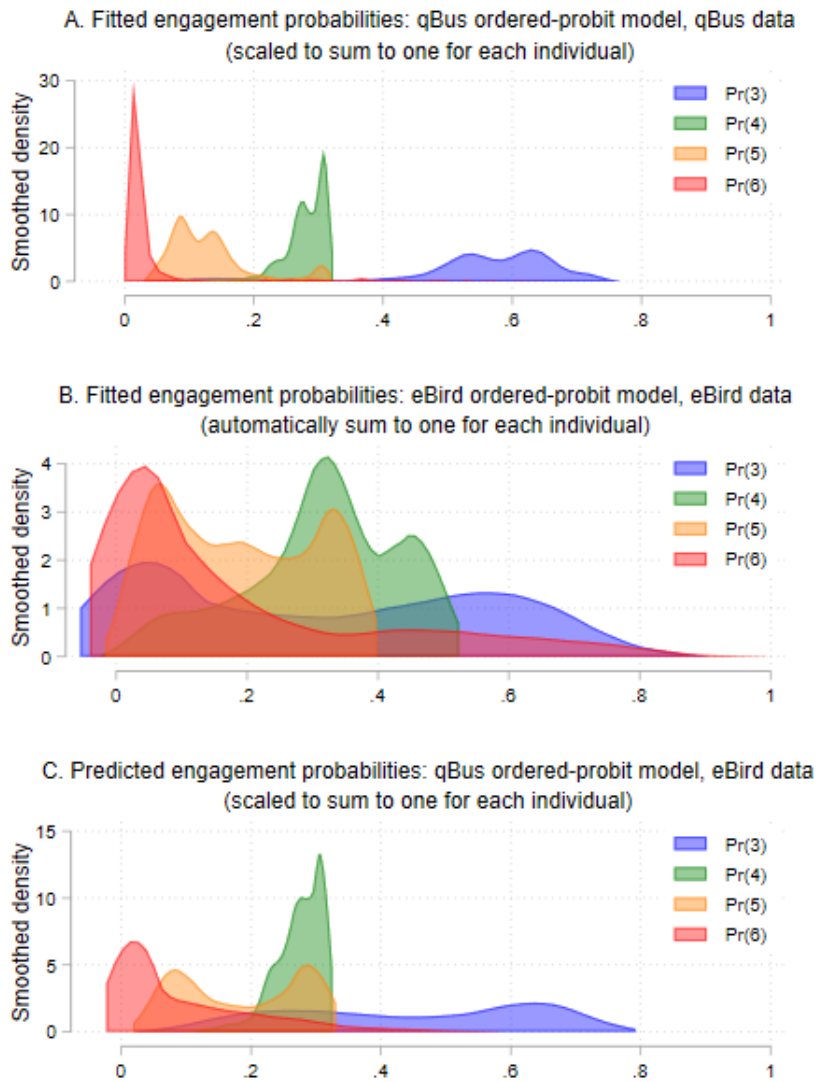

Figure A1: Color version of Figure 1 in the main text: Predicted probabilities for engagement levels 3, 4, 5, and 6. Panel A: fitted engagement level probabilities for qBus sample; Panel B: fitted engagement probabilities for the eBird sample; Panel C: predicted engagement probabilities for the eBird sample, based on an ordered-probit model estimated using the qBus sample.

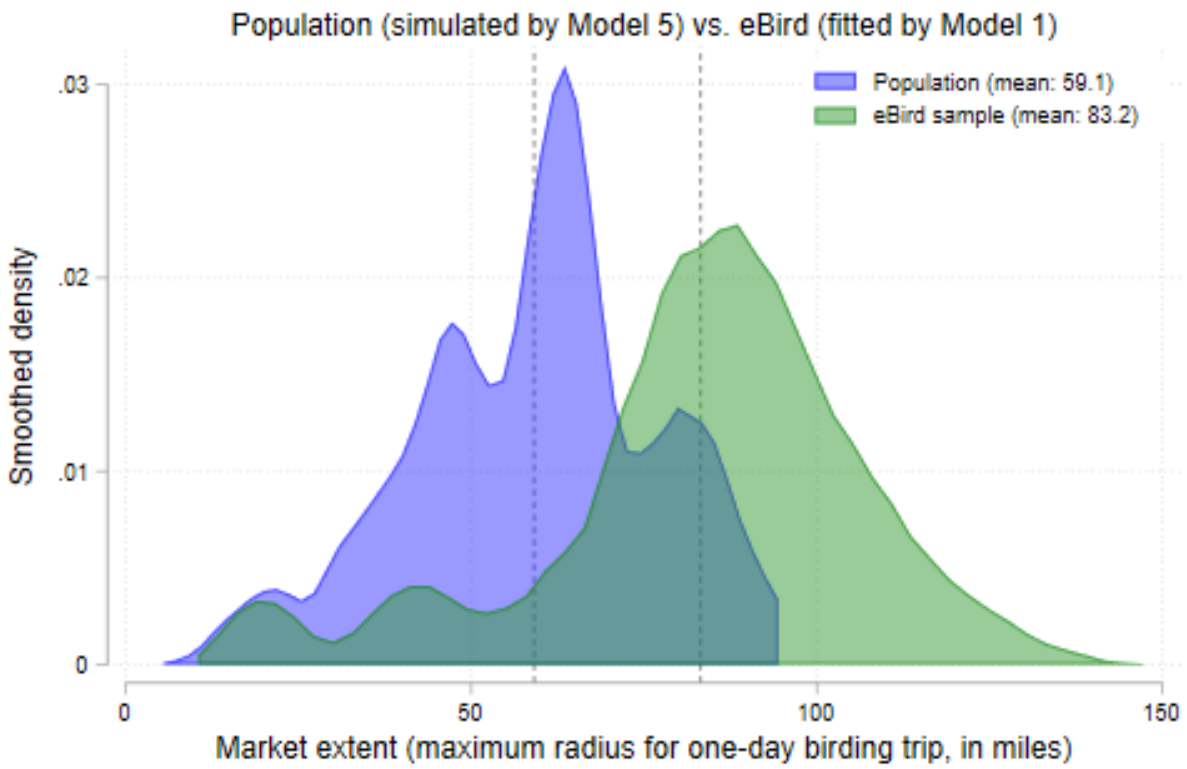

Figure A2: Color version of Figure 3 in the main text: For 1,081 eBird member survey observations: Marginal distribution of predicted consideration-set radii according to our naive Model 1 overlaid by selection-corrected predictions of these radii for (birders in) the general population based on Model 5.

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"Using Auxiliary Population Samples for Sample-Selection Correction in Models Based on Crowd-Sourced Volunteered Geographic Information" by Trudy Ann Cameron and Sonja Kolstoe

Appendices A - J

A Birding activity variables for qBus and engagement intensity options for both qBus and eBird samples

As detailed in Table 1 in the body of the paper, there are a number of notable differences between our two samples. For the annual number of days with trips of more than one mile to observe birds, we defined bins roughly according to decides of the qBus distribution between 1 and 364 days. Only 44% of the qBus sample responds to this question, but we can construct this variable for 77% of the eBird sample.[1] Our eBird respondents are less likely to have taken zero such trips, and more likely to claim to have traveled to see birds all 365 days of the year.

Our eBird member survey respondents are more likely to have participated in the Audubon Christmas Bird Count, and they are much less likely to hunt birds. They are somewhat more likely to be female and to be older.[2] A considerably larger share of the eBird member survey sample did not provide any income data (29.6 percent). Everyone in the eBird member survey sample is from the states of Washington and Oregon, whereas the qBus sample is nationwide. Compared to qBus respondents, more than twice as many eBird member survey respondents are retired. Finally, the eBird member survey sample reports higher educational attainment. All of these differences point to empirical evidence of systematic selection on observables, so that selection on unobservable factors is also likely to be a concern.

A summary of the engagement levels elicited in our two samples is provided in Table A2.

We note in the body of this paper that the Qualtrics Omnibus (qBus) survey we used to gather our general-population data has been discontinued. This appendix also includes Table A3, which lists selected survey research firms currently offering Omnibus surveys. The prices quoted are accurate for August of 2020, but may be adjusted over time by these firms. Surveys can be distributed to Mechanical Turk to a wide range of people, but mTurk samples are understood not to be representative of the general population, as confirmed recently by Walters et al. (2018), for example.

[1] To construct an analogous distribution for our eBird sample, we combine their actual number of days with submitted birding checklists over the preceding twelve months with their self-report as to what fraction of their bird sightings they report to eBird. The documented information about their actual trips distinguishes this constructed explanatory variable from the engagement intensities that form the outcome variable.

[2] They are also more likely to identify as White. However, the proportions of Black and Asian and Hispanic eBird respondents are all less than 1 percent, so we will not use the Race or Ethnicity indicators in our specifications.

Table A1: Share of 1050 qBus respondents reporting at least one day over the last year of engagement with the following wild-bird-related activities (response format: slider with labels at 0, 61, 122, 183, 243, 304 and 365 days); mean days per year and lower and upper quartiles of days. We find these counts to be rather high. This may be an artifact of using the Qualtrics' sliders to elicit numbers of days.

Description	N	At least 1 day	Mean days/ year	Lower quartile (days)	upper quartile (days)
Positive non-consumptive engagement with wild birds:					
Pause what you are doing to observe wild birds	999	0.881	92.8	10	161
Put out food for wild birds	960	0.783	98.4	3	181
Seek opportunities to learn more about wild birds	940	0.728	69.7	0	112
Photograph wild birds	945	0.747	68.5	0	107
Visit public parks/areas less than one mile from home to see, photograph or feed wild birds	926	0.703	67.2	0	109
Travel more than one mile from home to see, photograph or feed wild birds	914	0.667	62.4	0	90
— Any days, any of the above?	1050	0.878	-	-	-
Other interactions with wild birds:					
Employ measures to keep wild birds from harming your garden or property	910	0.624	60.3	0	92
Hunt wild birds for sport or for food	895	0.517	49.7	0	48

Table A2: Definitions and values of two eBird engagement variables for our two samples. CS is the dependent variable for the binary probit selection model; $CS6$ is the dependent variable for the six-level ordered-probit selection model ($CS6$ has four-levels for eBird sample).

eBird engagement bins	CS values	$CS6$ values	Observed for qBus general population sample?	Observed for eBird citizen science sample?
Does not know eBird	0	1	Y	N
Knows eBird, not a member	0	2	Y	N
Member, reports rarely	1	3	Y	Y
Member, reports $<$ half	1	4	Y	Y
Member, reports $>$ half	1	5	Y	Y
Member, reports almost all	1	6	Y	Y

Table A3: Selected Omnibus-type surveys (alphabetical), other than the Qualtrics Omnibus, available as of 8/2020

Survey firm	Product	Pricing (ca. 2020)	Available sociodemographic variables
Abacus Data (Canada)	National Omnibus Survey; At least 1,500 Canadian adults interviewed monthly; representative samples from large panels, statistical weighting according to the Census. Customization available: provincial oversamples, target audiences, etc.	1 to 3 questions: $1,000 per question	Included: Demographics (age, gender, education), household income, employment status and union membership, community type (urban, suburban, rural), Federal vote intention, 2015 federal vote choice.

Continued on next page

Table A3 – continued from previous page

AmeriSpeak (every two weeks)	AmeriSpeak Omnibus: 1000 responses; data file including weights and AmeriSpeak Omnibus Profile variables	Minimum of 3 survey question units: Per question: $1,000 (e.g. checklist with up to 10 response categories; grid questions using a rating scale with up to four attribute statements)	Included: One standard demographic banner table: age, gender, education, race/ethnicity, HH income (4 categories). For $300 extra: an additional profile variable (contact for available variables) All profile variables: Gender*, Age, Age (4 categories)*, Age (7 categories), Education (4 categories)*, Education (14 categories), Race/Ethnicity*, Household Size, Housing Type, Ownership of Living Quarters, Household Income (18 categories)*, Marital Status, Internet Access, Metropolitan Statistical Area Status, Region (U.S. Census - 4 categories), Region (U.S. Census - 9 categories), State, Household members, age 0-1, Household members, age 2-5, Household members, age 6-12, Household members, age 13-17, Household members, age 18+, Current Employment Status, Survey Start (date/time), Survey End (date/time), Survey Duration (minutes), Survey Mode (online/phone), Device Type (used to take survey). Note: * = Demographics variables included on the standard banner table
Drive Research	Census-representative sample; Excel file of raw responses in csv or SPSS format	1 to 2 questions, n=1000, $3,500; n-2000, $5,000; Additional questions at $200/question	Included: Up to four sociodemographic add-ons at no additional charge. Standard menu of sociodemographic questions: age, gender, household income, marital status, ethnicity, children in the household, education, employment, or region/state in the U.S. (If there is a question not on this list, they can check their respondent database/profiles to see if they can access it.)

Continued on next page

Table A3 – continued from previous page

Ipsos	KP Weekly Omnibus consists of 1,000 adults ages 18+; English only, fields weekly.	$1,000 each for questions 1-5; $800 each for questions 6-10; $400 each for questions 11+	Standard Profiling Variables (provided at no additional cost): Age, Education (highest degree received), Race/Ethnicity, Gender, Household Head, Household Size, Housing type, HH income - profile and imputed, Marital status, MSA Status (live in metro area or rural), Region 4 - Based On State Of Residence, Ownership status of living quarters, State, Total number of HH members age 1 or younger, Total number of HH members age 2 to 5, Total number of HH members age 6 to 12, Total number of HH members age 13 to 17, Total number of HH members age 18 or older.
YouGov (every 2 weeks, nationally representative)	Academic Omnibus: 1000 responses; codebook, dataset, with appended profile and weight variable	Setup: $500; Each single choice question: $500; Each 3-item matrix question: $750	Included: Birth year; Gender; Race; Education; Employment; Marital Status; Household Income; State of residence. For $500 extra, political demographics: vote registration, 2016 vote, party id, ideology, news interest, and the Pew religion battery

B Review Heckman's two-stage binary selection correction

For the $i = 1, ..., N$ individuals in our general population (qBus) sample, we have observations for some people who are members of eBird and other observations for other people who are not. For everyone, we have conformable variables on sociodemographics and income, Z_i, that we will use to explain eBird participation or non-participation, where respondents $i = 1, ..., r$ participate in eBird and respondents $i = s, ..., N$ do not:

$$CS_i = \begin{bmatrix} 1 \\ \vdots \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, Z_i = \begin{bmatrix} Z_{11} & \dots & Z_{k1} \\ \vdots & & \vdots \\ Z_{1r} & \dots & Z_{kr} \\ Z_{1s} & \dots & Z_{ks} \\ \vdots & & \vdots \\ Z_{1N} & \dots & Z_{kN} \end{bmatrix}$$

For the qBus sample, we model the latent propensity to be a member of eBird as $CS_i^* = Z_i\gamma + \eta_i$. We only have this data for the qBus sample, so we cannot estimate a second model to explain the outcome variable of interest, $y_i = X_i\beta + \epsilon$, because there are no data for our y_i variable of interest in the qBus sample.[3]

B.0.1 Binary selection and the eBird CS sample

For the $j = 1, ..., J$ observations from our eBird member survey sample, we have Z_j variables that conform to the Z_i variables in the qBus sample, but we have no information about anyone for whom $CS_j = 0$ (i.e. everyone in this sample is a member of eBird). In this case, the selection process cannot be modeled using the eBird data alone because there is no variation in the selection outcome for this group. However, we have data on an outcome variable of interest for this sample, y_j (in this case, the radius of the individual's consideration set, namely their maximum one-way distance for a one-day birding trip), and regressors, X_j, to explain this outcome, where this information is not available for the qBus sample:

$$CS_j = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}, Z_j = \begin{bmatrix} Z_{11} & \dots & Z_{k1} \\ \vdots & & \vdots \\ Z_{1J} & \dots & Z_{kJ} \end{bmatrix}, y_j = \begin{bmatrix} y_1 \\ \vdots \\ y_J \end{bmatrix}, X_j = \begin{bmatrix} X_{11} & \dots & X_{m1} \\ \vdots & & \vdots \\ Z_{1J} & \dots & Z_{mJ} \end{bmatrix}$$

For our eBird member survey sample, we assume the underlying relationship between CS and the Z variables is identical to the analogous relationship in the qBus sample. Our proposed selection-correction method will be appropriate if the identical γ and β parameters *would* apply in this eBird sample (and the same $\sigma_\eta, \sigma_\epsilon, \rho$, as well). If the selection equation

[3] That variable is collected only in our separate eBird member survey sample. A researcher could simply pose all the questions on our eBird member survey to a large sample of respondents from the general population. Then this would become a standard sample selection story which we outline in Appendix B.

could be estimated for the $j = 1, ..., J$ observations in the eBird member survey sample, the relevant pair of equations would be:

$$\begin{aligned} CS_j^* &= Z_j\gamma + \eta_j \\ y_j &= X_j\beta + \epsilon_j \\ (\eta_j, \epsilon_j) &\sim BVN(0, 0, \sigma_\eta, \sigma_\epsilon, \rho) \end{aligned} \tag{1}$$

Of course, this joint model cannot be estimated because the observed CS_j variable is constant (at 1) in the data from our eBird member survey. For the qBus general population panel, consider a binary indicator for eBird participation CS_i and a set of available regressors Z_i, for a representative sample. If we also had data, for these eBird participants, on an outcome variable of interest, y_i, and a set of regressors, X_i for a subset of this same sample, we would proceed as follows. Suppose the latent propensity to participate in eBird in this qBus sample is a linear-in-parameters function of the Z_i variables, $CS_i^* = Z_i\hat{\gamma} + \eta_i$, then the standard Heckman two-step sample-selection correction procedure involves two terms constructed from $Z_i\hat{\gamma}$.[4] Define:

$$\begin{aligned} \lambda\left(\alpha_{CS_i}\right) = \lambda\left(-Z_i\hat{\gamma}\right) &= \frac{\phi\left(-Z_i\hat{\gamma}\right)}{1 - \Phi\left(-Z_i\hat{\gamma}\right)} = \frac{\phi\left(Z_i\hat{\gamma}\right)}{\Phi\left(Z_i\hat{\gamma}\right)} \\ \delta\left(\alpha_{CS_i}\right) = \delta\left(-Z_i\hat{\gamma}\right) &= \lambda\left(-Z_i\hat{\gamma}\right)\left[\lambda\left(-Z_i\hat{\gamma}\right) - \left(-Z_i\hat{\gamma}\right)\right] \end{aligned} \tag{2}$$

With sample selection, the conditional expected value and the error variance of the outcome variable y_i are no longer given simply by $E\left[y_i\right] = X_i\beta$ and $Var\left[y_i\right] = \sigma_y^2$. Instead, we need the expected value and variance of the *marginal* distribution of y_i *conditional* on y_i being observed (i.e. when $CS_i = 1$). If we can assume that the latent propensity variable CS_i^* is distributed bivariate normal with the outcome variable y_i, but the joint distribution is truncated below at $-Z_i\hat{\gamma}$ in the CS_i^* dimension, the formulas for the expected value and variance of the relevant marginal distribution of y_i for this singly truncated bivariate normal distribution are as follows, as in Greene (2012, p. 836):

$$\begin{aligned} E\left[y_i|y_i \text{ observed}\right] &= E\left[y_i|CS_i^* > -Z_i\hat{\gamma}\right] = X_i\beta + \rho\sigma_\epsilon\lambda\left(-Z_i\hat{\gamma}\right) = X_i\beta + \beta_\lambda\lambda\left(-Z_i\hat{\gamma}\right) \\ Var\left[y_i|y_i \text{ observed}\right] &= Var\left[y_i|CS_i^* > -Z_i\hat{\gamma}\right] = \sigma_y^2\left[(1 - \rho^2\delta\left(-Z_i\hat{\gamma}\right)\right] \end{aligned} \tag{3}$$

These formulas provide the rationale for the Heckman two-step approach and why, once this augmented second-stage model has been estimated, we would have unbiased estimates of the expected value of y_i when y_i is observed under the counterfactual conditions where the correlation between the errors in these two equations is zero. For *uncorrelated* bivariate normal variables, the conditional distributions are everywhere equal to the marginal distribution, so we want to *simulate* the absence of any such error correlation. Based on the augmented regression model, therefore, we can set $\rho = 0$ to get:

$$\begin{aligned} E\left[y_i|y_i \text{ observed}\right] &= X_i\beta + (0\sigma_\epsilon)\lambda\left(-Z_i\hat{\gamma}\right) = X_i\beta \\ Var\left[y_i|y_i \text{ observed}\right] &= \sigma_y^2\left[(1 - (0)^2\delta\left(-Z_i\hat{\gamma}\right)\right] = \sigma_y^2 \end{aligned} \tag{4}$$

[4]Typically, however, attention is focused primarily on the λ term.

B.0.2 Sample-Selection Correction in the Related Literature

To date, the non-market valuation literature for environmental goods has focused mostly on correction strategies for when some surveys are not returned at all (called "unit" non-response), or for when the researcher cannot use some responses because those surveys are incomplete and one or more key variables are missing (called "item" non-response).

Standard econometric sample selection correction methods are familiar in the case of continuous outcome variables, as reviewed by Vella (1998) and Wooldridge (2002). However, sample-selection correction methods for multiple discrete outcomes are not particularly well developed in the environmental literature.[5] For conditional logit discrete-choice outcome models, Johnston and Abdulrahman (2017) use an ad hoc approach that builds on earlier work by Cameron and DeShazo (2013) to adjust for response propensity. Kolstoe and Cameron (2017) and Kolstoe et al. (2018) also use this approach, but employ the method to correct only for the individual's propensity to be in the estimating sample drawn from the population of eBird members, not the propensity to be an eBird member in the first place (see the Online Appendix from Kolstoe and Cameron (2017) for details).

Yuan et al. (2015) use a binary probit model to explain systematic selection into their estimating sample and compute a Heckman-style inverse Mills ratio (IMR). This IMR is used as a regressor in their second-stage conditional logit choice model, to shift the coefficient on the status-quo alternative in their choice sets.[6] However, a simple IMR term is appropriate only when the latent selection propensity variable and the (possibly transformed) outcome variable have a bivariate normal distribution. [7]

[5]Terza (2009) proposes a strategy for multinomial (multi-index) models, but does not illustrate his approach for the conditional logit models relevant to destination choice models or stated-preference choice experiments common in the environmental literature.

[6]Given that the IMR derived from the selection model is individual-specific but does not vary across alternatives, including it in the utility-difference "index" that underpins a conditional logit model requires that the IMR term be interacted with at least one regressor that actually *does* vary across alternatives. A status-quo indicator is one such variable.

[7]The Heckman logic for using an IMR thus does not apply when the outcome model is a conditional logit specification—one cannot appeal to the usual bivariate normality assumption for the errors in the two equations to argue that the inclusion of this IMR variable in the outcome equation precisely solves the problem of selection bias. Given that the bivariate normality assumption is untenable in the case of a conditional logit outcome model, there is no good argument for converting the selection propensity into an IMR term. In the present paper, however, we have a latent outcome variable that is plausibly normally distributed. In the observable data, however, this variable is reported in brackets, so an interval-data model based on a normal distribution for the logarithm of the dependent variable is reasonable.

C Use of Inverse Mills Ratios for sample selection correction

Over the last several decades, empirical researchers have become accustomed to the idea that estimating a sample-selection model via maximum likelihood methods, calculating the IMR, and including that estimated IMF into the desired "outcome" equation of interest will (somehow) purge the parameters of that outcome equation of any bias due to sample selection. However, it is crucial to remember that the IMR offers an appropriate correction for sample-selection bias only under some very specific conditions. Confidence that "including an IMR term" will "fix" selection bias hinges on the assumption that the selection equation and the outcome equation have error terms that are jointly normally distributed.

The joint normality assumption is critical because the IMR correction derives entirely from the formula for the expected value of a singly truncated bivariate normal distribution. If the conditional distribution latent variable in the selection equation is not normal or the conditional distribution of the dependent variable in the outcome equation is not normal (either observed or censored in some way, perhaps after some transformation), then the needed expected value of the singly truncated joint distribution of the errors in the selection equation and the outcome equation cannot automatically be assumed to be given by the usual IMR formulas.

Ideally, selection and outcome equations should be estimated jointly, in which case a wide variety of joint distributions for the two error terms can be assumed/employed, provided that the joint density can be derived and written down. In some cases, it is convenient to write the conditional joint distributions of the selection propensity and the outcome variable as the product of a conditional distribution and a marginal distribution.[8]

This insight is especially relevant for researchers who wish to estimate conditional logit "outcome" models based on people's choices across alternatives with different attributes. Nothing stops the analyst from estimating a binary probit sample selection model and calculating the usual IMR term from the fitted parameters. However, there is no rigorous statistical rationale for including this fitted IMR term like other respondent characteristics as a variable that might shift one or more slope characteristics or the coefficient on the status quo indicator variable, as is done in Yuan et al. (2015). Some types of joint models where IMR correction terms can make sense, statistically, include the following:

- The usual OLS outcome regression with a continuous dependent variable that is con-

[8]Stata now includes the "heckpoisson" estimator, following Terza (1998). Appropriately, this estimator is available only as a FIML estimator, not as a two-step estimator that relies on an IMR term. Jointly distributed variables that are not both normal have also been used in a FIML model that combines a participation/experience variable (that is distributed either Poisson or zero-inflated-Poisson) with a censored-normal outcome variable is estimated jointly in Cameron and Englin (1997).

ditionally normal, perhaps after some transformation

- A Tobit outcome model (censored anywhere—at the bottom, the top, or both) which involves a partially censored normal propensity variable
- An interval-data outcome variable censored between known thresholds (used in the present paper)
- An ordered-probit outcome model with a normally distributed latent propensity variable
- A censored normal outcome model with different censored points across observations

Simply appending an estimated IMR variable to a second-step outcome equation of interest cannot be assumed to be correct in any of the following cases:

- Count data models: Poisson, negative binomial
- Conditional logit models: fixed or random parameters
- Any other statistical model for the "outcome" equation, where the (perhaps latent) dependent is not conditionally normally distributed (even after transformation)

We note, however, the insights provided in Terza (2009), who describes a general approach to endogenous switching models, endogenous treatment models, and sample selection models. These techniques are extended versions of an approach proposed in Olsen (1980), suitable for within-sample corrections, but they seem not yet to have been widely employed in the empirical literture, especially in environmental economics. Should they become available as pre-coded general commands in commonly used software, these methods would likely be popular. However, they would need to be tailored specially for selection-model transfer exercises such as the two-step illustration in this paper.

D Weights based on predicted engagement intensities

In this section, we focus on the actual eBird members in the qBus sample, comparing their different participation levels to those in the entire eBird sample. With our eBird member survey data, there is the added concern that the *intensity* with which these survey respondents engage with the eBird citizen science project may not be representative of the distribution of eBird engagement propensities in the general population of the U.S. To address this issue, we consider how to develop weights for each of the four levels of participation intensity among these eBird members. We base our weights on the *fitted probabilities* of a respondent being each of the four engagement intensity bins in each sample.

For the qBus sample, we estimate an ordered probit model for all six possible bins and calculate a set of fitted probabilities for each bin for each person, conditional on the Z_i vector for that person. Call these probabilities $\hat{p}_{ki}$ for engagement levels $k = 1, ..., 6$.

We then make two calculations for each respondent in the eBird member survey sample. In the first calculation, we use the six-level engagement-intensity model estimated using the qBus data to predict (for the eBird member survey sample) the individual-specific set of six probabilities associated with each of the six engagement-intensity bins (even through nobody in the eBird sample is in non-participation bins 1 or 2). Call these fitted probabilities $\hat{p}^*_{kj}$ for engagement levels $k = 1, ..., 6$,

In the second calculation, we use the eBird sample independently, with its four possible participation-intensity bins. We estimate a four-level ordered-probit model using just the eBird member survey sample and calculate four fitted probabilities, which we will call $\hat{q}_{kj}$, for engagement levels $k = 3, ..., 6$ represented in that sample.

The next step is to assign weights to each respondent in the eBird dataset. These weights serve to scale the fitted probability of an individual being in their observed engagement-intensity bin to match the fitted probability in the population (i.e. the qBus sample). First, consider a hypothetical case where everyone in the qBus and eBird samples has been drawn from the same general population and people in both samples thus shared the same mixes of characteristics (i.e. had identical joint distributions for their Z variables). Then we would expect, across the two samples, to have roughly the same proportions of people in each engagement-intensity bin. However, since nobody in the eBird sample is observed in bins 1 or 2, we must focus on the portion of the engagement-intensity distribution corresponding to eBird membership. For the qBus sample, we should consider the probabilities of being in bins 3 through 6 for the qBus sample, *conditional* on the probability of being in at least one of those four bins. Thus we define $\hat{p}_{kj} = \hat{p}^*_{kj} / (\hat{p}^*_{3j} + \hat{p}^*_{4j} + \hat{p}^*_{5j} + \hat{p}^*_{6j})$.[9]

When we allow for potentially very different joint distributions of the explanatory variables Z_i and Z_j for the engagement-intensity model in the qBus and eBird samples, it is readily apparent that we should not use simply the differing observed *proportions* of people in each bin in the two samples to construct weights to be used in estimating the outcome model. Our preferred approach would be more akin to the common method of constructing

[9] An alternative would be to attempt to fit a four-level ordered probit for only the qBus respondents, but there are relatively few eBird members in the qBus sample.

exogenous weights based on age brackets or gender. We wish to allow multiple exogenous factors to affect *expected* levels of engagement intensity for each eBird respondent. Consequently, we weight each observation in the eBird sample by $\hat{p}_{kj}/\hat{q}_{kj}, k = 3, ..., 6$, normalized so that these weights sum to the sample size for the eBird sample. Use of these fitted probabilities recruits all of the exogenous or predetermined factors that capture heterogeneity in response propensities (i.e. the Z_i and Z_j data) to build the empirical weights, rather than just 0/1 group membership indicators.

E Dealing with missing values for Z_j variables in the eBird sample

E.1 qBus sociodemographic variables have few missing values

Any empirical application of this methodology may have to confront the problem of what to do when there are missing values of some variables in one sample or the other. If the correction is based upon the standard sociodemographic variables available for qBus panel members, the data for those variables can be expected to be relatively complete. Any missing values in the qBus sample might be expected to be missing at random.

If other key variables intended to serve as regressors, Z_i, used in our weighting strategy, are drawn from survey questions posed to qBus participants, it is entirely possible that there may be item non-response for some of those variables. Such is the case in the present study, where our own questions produced the data for the number of days per year on which the respondent traveled more than one mile to see birds. Our own questions also elicited the data for participation in the Christmas Bird count and whether the individual also hunts birds, but we assume in the case of these latter two variables that the few missing responses are quivalent to "no".

E.2 eBird sociodemographics match Census, but have more missing values

Missing values in the citizen-science eBird sample, for the sociodemographic variables that conform to the set available the qBus sample, are likely to be more of a problem. For example, due to time constraints for our survey of eBird members, we elected not to ask about individuals' political ideologies. Had we anticipated being able to employ qBus questions to build sampling weights and estimated response propensities, it would have been prudent to be sure that the citizen science members were asked *every* standard sociodemographic question, verbatim, that is available with the qBus responses.

For this first example of our procedure, we can assemble conformable measures for gender, race, ethnicity, broad income brackets, four regions of the U.S., employment status and educational attainment. Some aggregation of categories has been required in each sample to produce matching categories. In future applications of this method, it would be prudent to minimize this type of aggregation. In the eBird data, we used categories that matched the U.S. Census, which would facilitate more-conventional comparisons of marginal distributions in the eBird sample to marginal distributions in the general population. However, the U.S. Census does not provide any information about engagement in citizen science, so our special-purpose qBus general-population sample is much superior in that way.

E.3 Using maximal available Z_j regressors for each eBird observation

Suppose there were no data in the eBird sample on any of the same sociodemographic regressors, Z_i provided by the qBus sample. There would still be valuable information in the qBus sample that could help construct either probability weights or propensity corrections. If one runs an ordered probit model to explain the engagement outcome in the eBird data, but use *no* explanatory variables, the result is a set of estimates for only the three cut-points between the four outcome levels in in that eBird data. If one then calculates the predicted probabilities for each of the four participation intensities, the means of these probabilities, across the sample, match the proportions of the sample observed at each level.[10]

E.4 If there are no Z_j regressors available for some eBird respondents

If there were no Z_j regressors available for some (small) subset of observations in the eBird sample, the best available option for weighting the observations at each level of participation intensity would be derived solely from (a) the predicted probabilities for each of the four relevant participation-intensity levels in the qBus sample (also estimated without regressors) relative to (b) the analogous predicted probabilities for the same four participation intensity levels in the qBus sample. The implicit model being used to predict participation intensities, in that case, would have no Z regressors, so there would be no basis for observable systematic heterogeneity in these probabilities. The weights would then differ only across the four observed participation intensity levels, but would be the same for every person who had no available Z variables in the eBird sample.

E.5 If only some Z_j regressors are available for some eBird respondents

The most-general approach to weighting by participation intensity level or correcting parameters for different-from-average participation intensity would exploit the maximum information available in both samples, on an observation-by-observation basis for the eBird sample. To simplify, assume that only three basic factors are available as explanatory variables. In practice, each factor may be captured by a set of indicators for the categories of that factor, but we will assume for now that there is one continuous variable per factor such that the universe of potential Z variables consists of Z_1, Z_2, and Z_3. All three variables (standing in for groups of indicator variables) are available for each qBus observation, but different

[10]For binary probit and logit models, the means of the fitted probabilities will be either extremely close to the observed proportions, or exactly equal to those proportions, as can be proven by the algebra of the first-order conditions for the maximum likelihood estimation algorithm.

observations in the eBird sample have missing values for either one, two, or all three of these variables.

To fully exploit the available information, it is necessary to estimate an array of models for the qBus sample so that one of these models will be appropriate to transfer to every observation in the eBird sample. Suppose that we have indicators for the presence or absence of values for each of these three Z variables in the eBird sample. The number of necessary models using the qBus data could then be calculated using the sum of all the relevant combinations:

$$C_0^3 + C_1^3 + C_2^3 + C_3^3 = 1 + 3 + 3 + 1 = 8 \tag{5}$$

Of course, as the number of potential factors increases, the number of potentially relevant models to explain participation intensities in the qBus data can increase dramatically. In this study, we have six different factors with complete data in the qBus sample but missing data for at least some observations in the eBird sample: gender, age, income, region, employment status, and education. The number of potentially relevant models could be 64, but due to the correlation between missing values for some of these factors, the actual number of models required is only 30 in this study.

Table A4: Ordered-probit engagement-level models with minimum heterogeneity required to accommodate entire eBird sample: estimated using qBus sample, full eBird sample. Region variable is "West" for all eBird respondents.

	Ordered probit qBus data		Ordered probit eBird data	
Has participated in CBC	2.202***	(0.0670)	0.487***	(0.0678)
Hunts birds	0.526***	(0.0504)	0.0400	(0.128)
Region: Northeast	0.170**	(0.0697)	- [a]	
Region: Midwest	-0.0668	(0.0713)	- [a]	
Region: South	-0.0335	(0.0623)	- [a]	
cut1	1.271***	(0.0525)	-0.0249	(0.0527)
cut2	1.814***	(0.0575)	0.715***	(0.0552)
cut3	2.136***	(0.0622)	1.320***	(0.0623)
cut4	2.527***	(0.0687)	- [b]	
cut5	3.142***	(0.0819)	- [b]	
Observations	4161		1081	
Max. log-likelihood	-2591.22		-1396.30	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ [a]Var = 0 for all. [b]Only 4 levels.

F Six-level ordered-probit eBird engagement-level models for all relevant subsets of regressors (using data from the qBus sample)

Table A5: qBus sample: Model 1-3 (of 30) to accommodate eBird missing values

	Model 1	Model 2	Model 3
Engagement-level indicator			
Has participated in CBC	2.202***	2.144***	2.120***
	(0.0670)	(0.0679)	(0.0682)
Hunts birds	0.526***	0.520***	0.526***
	(0.0504)	(0.0509)	(0.0514)
Region: Northeast	0.170**	0.162**	0.145**
	(0.0697)	(0.0705)	(0.0707)
Region: Midwest	-0.0668	-0.0596	-0.0580
	(0.0713)	(0.0721)	(0.0722)
Region: South	-0.0335	-0.0190	-0.0135
	(0.0623)	(0.0631)	(0.0633)
Empl. status: Part time		0.0240	0.0508
		(0.0674)	(0.0684)
Empl. status: Looking for work		-0.133	-0.106
		(0.101)	(0.102)
Empl. status: Unemployed		-0.151**	-0.120
		(0.0711)	(0.0737)
Empl. status: Retired		-0.632***	-0.638***
		(0.0800)	(0.0805)
Education: High school			0.0424
			(0.0688)
Education: Some college			-0.102
			(0.0628)
Education: Masters degree			0.244***

Continued on next page

Table A5 – continued from previous page

			(0.0784)
Education: Doctoral degree			0.209*
			(0.118)
/			
cut1	1.271***	1.150***	1.171***
	(0.0525)	(0.0581)	(0.0682)
cut2	1.814***	1.704***	1.728***
	(0.0575)	(0.0626)	(0.0722)
cut3	2.136***	2.032***	2.061***
	(0.0622)	(0.0670)	(0.0762)
cut4	2.527***	2.431***	2.465***
	(0.0687)	(0.0729)	(0.0816)
cut5	3.142***	3.054***	3.096***
	(0.0819)	(0.0852)	(0.0931)
Observations	4161	4161	4161
Max. log-likelihood	-2591.22	-2553.34	-2541.62

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Model 4	Model 5	Model 6
Engagement-level indicator			
Has participated in CBC	2.023***	2.166***	2.132***
	(0.0691)	(0.0676)	(0.0680)
Hunts birds	0.508***	0.535***	0.520***
	(0.0522)	(0.0510)	(0.0509)
Age: 24 years or less	0.534***		
	(0.0964)		
Age: 25 to 34 years	0.560***		
	(0.0847)		
Age: 35 to 44 years	0.389***		
	(0.0873)		
Age: 55 to 64 years	-0.239**		
	(0.107)		
Age: 65 years and up	-0.328**		
	(0.131)		
Region: Northeast	0.162**	0.158**	0.166**
	(0.0718)	(0.0701)	(0.0706)
Region: Midwest	-0.0513	-0.0621	-0.0517
	(0.0735)	(0.0714)	(0.0721)
Region: South	0.00627	-0.0248	-0.0109
	(0.0643)	(0.0625)	(0.0632)
Empl. status: Part time	0.00864		0.0495
	(0.0719)		(0.0681)
Empl. status: Looking for work	-0.194*		-0.110
	(0.104)		(0.101)
Empl. status: Unemployed	-0.166**		-0.112
	(0.0755)		(0.0725)
Empl. status: Retired	-0.138		-0.633***

Continued on next page

Table A6 – continued from previous page

	(0.104)		(0.0799)
Education: High school	-0.0213	0.0227	
	(0.0709)	(0.0663)	
Education: Some college	-0.144**	-0.105*	
	(0.0644)	(0.0617)	
Education: Masters degree	0.269***	0.208***	
	(0.0798)	(0.0775)	
Education: Doctoral degree	0.204*	0.162	
	(0.119)	(0.116)	
Gender: Female		-0.0946**	-0.135***
		(0.0472)	(0.0484)
/			
cut1	1.441***	1.226***	1.097***
	(0.0967)	(0.0680)	(0.0609)
cut2	2.021***	1.772***	1.652***
	(0.100)	(0.0720)	(0.0652)
cut3	2.365***	2.098***	1.981***
	(0.103)	(0.0758)	(0.0694)
cut4	2.780***	2.495***	2.382***
	(0.108)	(0.0812)	(0.0750)
cut5	3.421***	3.120***	3.007***
	(0.118)	(0.0928)	(0.0868)
Observations	4161	4161	4161
Max. log-likelihood	-2477.40	-2578.51	-2549.44

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Model 7	Model 8	Model 9
Engagement-level indicator			
Has participated in CBC	2.111***	2.050***	2.015***
	(0.0683)	(0.0685)	(0.0689)
Hunts birds	0.525***	0.488***	0.505***
	(0.0514)	(0.0516)	(0.0522)
Gender: Female	-0.116**	-0.212***	-0.188***
	(0.0487)	(0.0484)	(0.0488)
Region: Northeast	0.149**	0.187***	0.168**
	(0.0708)	(0.0716)	(0.0719)
Region: Midwest	-0.0513	-0.0368	-0.0382
	(0.0723)	(0.0733)	(0.0735)
Region: South	-0.00677	0.0173	0.0193
	(0.0633)	(0.0641)	(0.0643)
Empl. status: Part time	0.0715		
	(0.0690)		
Empl. status: Looking for work	-0.0876		
	(0.102)		
Empl. status: Unemployed	-0.0878		
	(0.0749)		
Empl. status: Retired	-0.638***		
	(0.0805)		
Education: High school	0.0415		-0.0593
	(0.0688)		(0.0690)
Education: Some college	-0.0957		-0.149**
	(0.0629)		(0.0638)
Education: Masters degree	0.239***		0.266***
	(0.0784)		(0.0799)
Education: Doctoral degree	0.190		0.176

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Table A7 – continued from previous page

	(0.118)		(0.120)
Age: 24 years or less		0.492***	0.542***
		(0.0926)	(0.0937)
Age: 25 to 34 years		0.574***	0.578***
		(0.0837)	(0.0841)
Age: 35 to 44 years		0.407***	0.399***
		(0.0866)	(0.0870)
Age: 55 to 64 years		-0.270***	-0.269**
		(0.105)	(0.105)
Age: 65 years and up		-0.375***	-0.422***
		(0.113)	(0.114)
/			
cut1	1.125***	1.404***	1.390***
	(0.0707)	(0.0894)	(0.0980)
cut2	1.683***	1.979***	1.970***
	(0.0746)	(0.0929)	(0.101)
cut3	2.016***	2.320***	2.316***
	(0.0784)	(0.0963)	(0.104)
cut4	2.422***	2.730***	2.733***
	(0.0835)	(0.101)	(0.109)
cut5	3.055***	3.362***	3.375***
	(0.0947)	(0.111)	(0.119)
Observations	4161	4161	4161
Max. log-likelihood	-2538.76	-2489.65	-2474.54

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Model 10	Model 11	Model 12
Engagement-level indicator			
Has participated in CBC	2.034***	2.006***	2.016***
	(0.0690)	(0.0693)	(0.0691)
Hunts birds	0.495***	0.507***	0.505***
	(0.0517)	(0.0522)	(0.0522)
Gender: Female	-0.192***	-0.176***	-0.184***
	(0.0494)	(0.0497)	(0.0492)
Age: 24 years or less	0.510***	0.543***	0.551***
	(0.0959)	(0.0966)	(0.0947)
Age: 25 to 34 years	0.569***	0.572***	0.581***
	(0.0846)	(0.0849)	(0.0846)
Age: 35 to 44 years	0.400***	0.392***	0.399***
	(0.0871)	(0.0875)	(0.0870)
Age: 55 to 64 years	-0.251**	-0.252**	-0.271***
	(0.107)	(0.107)	(0.105)
Age: 65 years and up	-0.307**	-0.361***	-0.426***
	(0.130)	(0.132)	(0.114)
Region: Northeast	0.187***	0.168**	0.171**
	(0.0717)	(0.0720)	(0.0720)
Region: Midwest	-0.0398	-0.0396	-0.0349
	(0.0734)	(0.0736)	(0.0736)
Region: South	0.0146	0.0183	0.0225
	(0.0643)	(0.0645)	(0.0645)
Empl. status: Part time	0.00659	0.0390	
	(0.0719)	(0.0727)	
Empl. status: Looking for work	-0.204**	-0.169	
	(0.104)	(0.105)	
Empl. status: Unemployed	-0.162**	-0.121	

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Table A8 – continued from previous page

	(0.0744)	(0.0767)	
Empl. status: Retired	-0.143	-0.116	
	(0.103)	(0.104)	
Education: High school		-0.0276	-0.0472
		(0.0710)	(0.0731)
Education: Some college		-0.138**	-0.147**
		(0.0645)	(0.0654)
Education: Masters degree		0.263***	0.270***
		(0.0799)	(0.0810)
Education: Doctoral degree		0.175	0.178
		(0.120)	(0.122)
Income: Less than 25K			-0.0820
			(0.0815)
Income: 25 K to 50 K			-0.0137
			(0.0755)
Income: 75 K to 100 K			-0.0489
			(0.0845)
Income: 100 K or more			-0.0310
			(0.0762)
/			
cut1	1.367***	1.373***	1.367***
	(0.0908)	(0.0985)	(0.109)
cut2	1.943***	1.954***	1.948***
	(0.0942)	(0.102)	(0.112)
cut3	2.284***	2.300***	2.293***
	(0.0975)	(0.105)	(0.115)
cut4	2.696***	2.718***	2.711***
	(0.102)	(0.110)	(0.119)
cut5	3.331***	3.362***	3.352***

Continued on next page

Table A8 – continued from previous page

	(0.112)	(0.119)	(0.129)
Observations	4161	4161	4161
Max. log-likelihood	-2484.82	-2471.15	-2473.89

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: qBus sample: Model 13-15 (of 30) to accommodate eBird missing values

	Model 13	Model 14	Model 15
Engagement-level indicator			
Has participated in CBC	2.032***	2.008***	2.075***
	(0.0691)	(0.0694)	(0.0685)
Hunts birds	0.500***	0.506***	0.0780
	(0.0518)	(0.0523)	(0.0941)
Gender: Female	-0.186***	-0.175***	
	(0.0496)	(0.0499)	
Age: 24 years or less	0.526***	0.545***	
	(0.0966)	(0.0971)	
Age: 25 to 34 years	0.582***	0.572***	
	(0.0850)	(0.0854)	
Age: 35 to 44 years	0.399***	0.393***	
	(0.0871)	(0.0875)	
Age: 55 to 64 years	-0.258**	-0.254**	
	(0.107)	(0.107)	
Age: 65 years and up	-0.322**	-0.366***	
	(0.130)	(0.132)	
Income: Less than 25K	-0.0569	-0.0542	
	(0.0826)	(0.0840)	
Income: 25 K to 50 K	-0.0201	-0.0107	
	(0.0755)	(0.0758)	
Income: 75 K to 100 K	-0.00868	-0.0514	
	(0.0838)	(0.0846)	
Income: 100 K or more	0.0624	-0.0345	
	(0.0729)	(0.0763)	
Region: Northeast	0.188***	0.170**	0.158**
	(0.0718)	(0.0721)	(0.0715)
Region: Midwest	-0.0409	-0.0363	-0.0540

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Table A9 – continued from previous page

	(0.0736)	(0.0738)	(0.0731)
Region: South	0.0182	0.0203	0.000262
	(0.0644)	(0.0647)	(0.0638)
Empl. status: Part time	0.0255	0.0431	
	(0.0734)	(0.0737)	
Empl. status: Looking for work	-0.178*	-0.163	
	(0.106)	(0.106)	
Empl. status: Unemployed	-0.135*	-0.112	
	(0.0778)	(0.0790)	
Empl. status: Retired	-0.122	-0.114	
	(0.104)	(0.105)	
Education: High school		-0.0267	
		(0.0740)	
Education: Some college		-0.141**	
		(0.0658)	
Education: Masters degree		0.269***	
		(0.0810)	
Education: Doctoral degree		0.178	
		(0.122)	
Travel 1+ mile data available			0.354
			(0.688)
Trips 1+ miles = 0			-1.072
			(0.693)
Trips 1+ miles = [1,4)			-0.674
			(0.703)
Trips 1+ miles = [4,7)			-0.892
			(0.707)
Trips 1+ miles = [7,10)			-0.600

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Table A9 – continued from previous page

			(0.705)
Trips 1+ miles = [10,21)			-0.309
			(0.693)
Trips 1+ miles = [21,41)			-0.284
			(0.695)
Trips 1+ miles = [41,72)			0.0561
			(0.692)
Trips 1+ miles = [72,124)			0.293
			(0.690)
Trips 1+ miles = [124,174)			0.212
			(0.689)
Trips 1+ miles = [174,238)			0.341
			(0.689)
Trips 1+ miles = [238,364)			0.634
			(0.689)
Trips 1+ miles = 365			0.579
			(0.714)
/			
cut1	1.386***	1.349***	1.188***
	(0.102)	(0.110)	(0.0558)
cut2	1.963***	1.930***	1.769***
	(0.105)	(0.113)	(0.0610)
cut3	2.304***	2.276***	2.112***
	(0.108)	(0.115)	(0.0658)
cut4	2.718***	2.694***	2.518***
	(0.113)	(0.120)	(0.0722)
cut5	3.354***	3.337***	3.143***
	(0.122)	(0.129)	(0.0849)
Observations	4161	4161	4161
Max. log-likelihood	-2483.54	-2470.79	-2490.38

Continued on next page

Table A9 – continued from previous page

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: qBus sample: Model 16-18 (of 30) to accommodate eBird missing values

	Model 16	Model 17	Model 18
Engagement-level indicator			
Travel 1+ mile data available	0.299	0.242	0.183
	(0.674)	(0.673)	(0.689)
Trips 1+ miles = 0	-1.017	-0.963	-0.921
	(0.679)	(0.678)	(0.694)
Trips 1+ miles = [1,4)	-0.625	-0.485	-0.313
	(0.689)	(0.688)	(0.705)
Trips 1+ miles = [4,7)	-0.852	-0.787	-0.590
	(0.693)	(0.693)	(0.709)
Trips 1+ miles = [7,10)	-0.551	-0.528	-0.442
	(0.691)	(0.691)	(0.708)
Trips 1+ miles = [10,21)	-0.264	-0.207	-0.105
	(0.679)	(0.678)	(0.694)
Trips 1+ miles = [21,41)	-0.240	-0.144	-0.0796
	(0.681)	(0.679)	(0.696)
Trips 1+ miles = [41,72)	0.0970	0.132	0.229
	(0.678)	(0.676)	(0.692)
Trips 1+ miles = [72,124)	0.356	0.415	0.461
	(0.676)	(0.674)	(0.690)
Trips 1+ miles = [124,174)	0.272	0.295	0.335
	(0.675)	(0.674)	(0.690)
Trips 1+ miles = [174,238)	0.382	0.441	0.451
	(0.675)	(0.673)	(0.689)
Trips 1+ miles = [238,364)	0.666	0.711	0.703
	(0.674)	(0.673)	(0.689)
Trips 1+ miles = 365	0.623	0.630	0.649
	(0.700)	(0.698)	(0.714)

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Table A10 – continued from previous page

Has participated in CBC	2.049***	2.003***	1.959***
	(0.0689)	(0.0696)	(0.0699)
Hunts birds	0.0977	0.0874	0.0524
	(0.0943)	(0.0949)	(0.0962)
Region: Northeast	0.143**	0.137*	0.175**
	(0.0718)	(0.0725)	(0.0731)
Region: Midwest	-0.0537	-0.0401	-0.0356
	(0.0733)	(0.0740)	(0.0749)
Region: South	0.00426	0.0225	0.0340
	(0.0640)	(0.0647)	(0.0654)
Education: High school	-0.00150	0.0284	
	(0.0677)	(0.0702)	
Education: Some college	-0.103	-0.0925	
	(0.0631)	(0.0643)	
Education: Masters degree	0.222***	0.250***	
	(0.0792)	(0.0801)	
Education: Doctoral degree	0.176	0.205*	
	(0.119)	(0.120)	
Empl. status: Part time		0.0552	-0.0301
		(0.0698)	(0.0725)
Empl. status: Looking for work		-0.127	-0.246**
		(0.105)	(0.105)
Empl. status: Unemployed		-0.116	-0.212***
		(0.0752)	(0.0747)
Empl. status: Retired		-0.612***	-0.209**
		(0.0832)	(0.105)
Age: 24 years or less			0.491***
			(0.0977)
Age: 25 to 34 years			0.526***

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Table A10 – continued from previous page

			(0.0861)
Age: 35 to 44 years			0.364***
			(0.0888)
Age: 55 to 64 years			-0.186*
			(0.109)
Age: 65 years and up			-0.198
			(0.131)
/			
cut1	1.185***	1.096***	1.354***
	(0.0684)	(0.0717)	(0.0917)
cut2	1.769***	1.691***	1.963***
	(0.0728)	(0.0759)	(0.0954)
cut3	2.115***	2.043***	2.319***
	(0.0770)	(0.0800)	(0.0989)
cut4	2.527***	2.463***	2.741***
	(0.0826)	(0.0853)	(0.104)
cut5	3.160***	3.104***	3.381***
	(0.0941)	(0.0964)	(0.113)
Observations	4161	4161	4161
Max. log-likelihood	-2480.49	-2446.81	-2410.56

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A11: qBus sample: Model 19-21 (of 30) to accommodate eBird missing values

	Model 19	Model 20	Model 21
Engagement-level indicator			
Travel 1+ mile data available	0.127	0.166	0.146
	(0.671)	(0.666)	(0.670)
Trips 1+ miles = 0	-0.867	-0.905	-0.885
	(0.677)	(0.672)	(0.676)
Trips 1+ miles = [1,4)	-0.261	-0.295	-0.276
	(0.688)	(0.683)	(0.686)
Trips 1+ miles = [4,7)	-0.549	-0.577	-0.569
	(0.692)	(0.687)	(0.691)
Trips 1+ miles = [7,10)	-0.396	-0.408	-0.414
	(0.691)	(0.685)	(0.690)
Trips 1+ miles = [10,21)	-0.0601	-0.0922	-0.0801
	(0.677)	(0.672)	(0.676)
Trips 1+ miles = [21,41)	-0.0278	-0.0705	-0.0441
	(0.678)	(0.673)	(0.677)
Trips 1+ miles = [41,72)	0.275	0.243	0.260
	(0.675)	(0.670)	(0.673)
Trips 1+ miles = [72,124)	0.527	0.494	0.510
	(0.673)	(0.668)	(0.672)
Trips 1+ miles = [124,174)	0.397	0.363	0.381
	(0.673)	(0.667)	(0.671)
Trips 1+ miles = [174,238)	0.489	0.447	0.470
	(0.672)	(0.667)	(0.671)
Trips 1+ miles = [238,364)	0.731	0.690	0.711
	(0.671)	(0.666)	(0.670)
Trips 1+ miles = 365	0.697	0.688	0.685
	(0.697)	(0.692)	(0.696)

Continued on next page

Table A11 – continued from previous page

Has participated in CBC	1.929***	1.943***	1.930***
	(0.0703)	(0.0700)	(0.0704)
Hunts birds	0.0730	0.0678	0.0728
	(0.0964)	(0.0963)	(0.0964)
Age: 24 years or less	0.527***	0.534***	0.534***
	(0.0984)	(0.0964)	(0.0989)
Age: 25 to 34 years	0.530***	0.545***	0.536***
	(0.0864)	(0.0861)	(0.0869)
Age: 35 to 44 years	0.358***	0.365***	0.358***
	(0.0892)	(0.0887)	(0.0892)
Age: 55 to 64 years	-0.192*	-0.226**	-0.196*
	(0.110)	(0.107)	(0.110)
Age: 65 years and up	-0.262**	-0.358***	-0.269**
	(0.133)	(0.117)	(0.134)
Region: Northeast	0.156**	0.160**	0.159**
	(0.0734)	(0.0734)	(0.0735)
Region: Midwest	-0.0333	-0.0303	-0.0306
	(0.0751)	(0.0752)	(0.0753)
Region: South	0.0398	0.0453	0.0441
	(0.0656)	(0.0657)	(0.0659)
Empl. status: Part time	0.00414		0.0151
	(0.0733)		(0.0745)
Empl. status: Looking for work	-0.207*		-0.193*
	(0.106)		(0.108)
Empl. status: Unemployed	-0.165**		-0.148*
	(0.0770)		(0.0794)
Empl. status: Retired	-0.177*		-0.167
	(0.106)		(0.107)
Education: High school	-0.0321	-0.0444	-0.0177

Continued on next page

Table A11 – continued from previous page

	(0.0722)	(0.0743)	(0.0752)
Education: Some college	-0.137**	-0.140**	-0.130*
	(0.0657)	(0.0667)	(0.0671)
Education: Masters degree	0.275***	0.274***	0.273***
	(0.0812)	(0.0824)	(0.0824)
Education: Doctoral degree	0.201*	0.189	0.191
	(0.122)	(0.124)	(0.124)
Income: Less than 25K		-0.111	-0.0713
		(0.0825)	(0.0851)
Income: 25 K to 50 K		-0.0287	-0.0229
		(0.0770)	(0.0773)
Income: 75 K to 100 K		-0.0328	-0.0362
		(0.0865)	(0.0866)
Income: 100 K or more		0.00665	0.0000751
		(0.0779)	(0.0781)
/			
cut1	1.357***	1.380***	1.349***
	(0.0997)	(0.110)	(0.111)
cut2	1.970***	1.993***	1.963***
	(0.103)	(0.113)	(0.114)
cut3	2.332***	2.355***	2.324***
	(0.107)	(0.116)	(0.117)
cut4	2.761***	2.782***	2.754***
	(0.111)	(0.121)	(0.122)
cut5	3.409***	3.428***	3.402***
	(0.121)	(0.130)	(0.131)
Observations	4161	4161	4161
Max. log-likelihood	-2396.30	-2400.01	-2395.83

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: qBus sample: Model 22-24 (of 30) to accommodate eBird missing values

	Model 22	Model 23	Model 24
Engagement-level indicator			
Travel 1+ mile data available	0.343	0.295	0.241
	(0.679)	(0.668)	(0.666)
Trips 1+ miles = 0	-1.062	-1.013	-0.958
	(0.685)	(0.674)	(0.671)
Trips 1+ miles = [1,4)	-0.664	-0.621	-0.481
	(0.694)	(0.684)	(0.681)
Trips 1+ miles = [4,7)	-0.885	-0.850	-0.787
	(0.698)	(0.687)	(0.686)
Trips 1+ miles = [7,10)	-0.580	-0.539	-0.517
	(0.697)	(0.686)	(0.684)
Trips 1+ miles = [10,21)	-0.289	-0.251	-0.196
	(0.685)	(0.674)	(0.671)
Trips 1+ miles = [21,41)	-0.264	-0.228	-0.132
	(0.686)	(0.675)	(0.673)
Trips 1+ miles = [41,72)	0.0791	0.112	0.146
	(0.683)	(0.672)	(0.669)
Trips 1+ miles = [72,124)	0.303	0.358	0.415
	(0.681)	(0.670)	(0.667)
Trips 1+ miles = [124,174)	0.231	0.283	0.305
	(0.681)	(0.670)	(0.667)
Trips 1+ miles = [174,238)	0.357	0.391	0.448
	(0.680)	(0.669)	(0.667)
Trips 1+ miles = [238,364)	0.649	0.675	0.720
	(0.680)	(0.669)	(0.666)
Trips 1+ miles = 365	0.590	0.629	0.634
	(0.705)	(0.695)	(0.692)

Continued on next page

Table A12 – continued from previous page

Has participated in CBC	2.060***	2.038***	1.994***
	(0.0688)	(0.0691)	(0.0697)
Hunts birds	0.0756	0.0937	0.0816
	(0.0940)	(0.0943)	(0.0949)
Gender: Female	-0.128***	-0.104**	-0.120**
	(0.0478)	(0.0484)	(0.0498)
Region: Northeast	0.162**	0.147**	0.141*
	(0.0716)	(0.0719)	(0.0726)
Region: Midwest	-0.0460	-0.0472	-0.0326
	(0.0732)	(0.0733)	(0.0741)
Region: South	0.00866	0.0109	0.0300
	(0.0639)	(0.0640)	(0.0648)
Education: High school		0.00516	0.0277
		(0.0679)	(0.0703)
Education: Some college		-0.0931	-0.0858
		(0.0632)	(0.0643)
Education: Masters degree		0.215***	0.244***
		(0.0793)	(0.0801)
Education: Doctoral degree		0.156	0.184
		(0.119)	(0.120)
Empl. status: Part time			0.0766
			(0.0705)
Empl. status: Looking for work			-0.108
			(0.105)
Empl. status: Unemployed			-0.0833
			(0.0765)
Empl. status: Retired			-0.610***
			(0.0831)
/			
cut1	1.128***	1.140***	1.051***

Continued on next page

Table A12 – continued from previous page

	(0.0599)	(0.0714)	(0.0740)
cut2	1.711***	1.725***	1.646***
	(0.0647)	(0.0756)	(0.0781)
cut3	2.054***	2.071***	1.999***
	(0.0691)	(0.0796)	(0.0820)
cut4	2.462***	2.484***	2.421***
	(0.0751)	(0.0849)	(0.0871)
cut5	3.091***	3.120***	3.063***
	(0.0872)	(0.0960)	(0.0979)
Observations	4161	4161	4161
Max. log-likelihood	-2486.77	-2478.16	-2443.92

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A13: qBus sample: Model 25-27 (of 30) to accommodate eBird missing values

	Model 25	Model 26	Model 27
Engagement-level indicator			
Travel 1+ mile data available	0.125	0.170	0.122
	(0.659)	(0.676)	(0.662)
Trips 1+ miles = 0	-0.858	-0.904	-0.856
	(0.665)	(0.681)	(0.668)
Trips 1+ miles = [1,4)	-0.250	-0.296	-0.249
	(0.676)	(0.692)	(0.679)
Trips 1+ miles = [4,7)	-0.527	-0.571	-0.537
	(0.681)	(0.696)	(0.683)
Trips 1+ miles = [7,10)	-0.350	-0.412	-0.373
	(0.679)	(0.695)	(0.682)
Trips 1+ miles = [10,21)	-0.0324	-0.0784	-0.0411
	(0.665)	(0.681)	(0.668)
Trips 1+ miles = [21,41)	-0.0168	-0.0510	-0.00610
	(0.666)	(0.683)	(0.669)
Trips 1+ miles = [41,72)	0.300	0.260	0.300
	(0.663)	(0.679)	(0.665)
Trips 1+ miles = [72,124)	0.533	0.471	0.531
	(0.661)	(0.677)	(0.664)
Trips 1+ miles = [124,174)	0.412	0.359	0.413
	(0.661)	(0.677)	(0.663)
Trips 1+ miles = [174,238)	0.495	0.469	0.501
	(0.660)	(0.676)	(0.663)
Trips 1+ miles = [238,364)	0.741	0.724	0.745
	(0.659)	(0.676)	(0.662)
Trips 1+ miles = 365	0.723	0.664	0.708
	(0.686)	(0.702)	(0.688)

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Table A13 – continued from previous page

Has participated in CBC	1.923***	1.941***	1.913***
	(0.0701)	(0.0701)	(0.0704)
Hunts birds	0.0591	0.0436	0.0642
	(0.0963)	(0.0963)	(0.0965)
Gender: Female	-0.184***	-0.187***	-0.171***
	(0.0498)	(0.0503)	(0.0507)
Age: 24 years or less	0.534***	0.501***	0.535***
	(0.0957)	(0.0980)	(0.0987)
Age: 25 to 34 years	0.549***	0.538***	0.542***
	(0.0857)	(0.0863)	(0.0866)
Age: 35 to 44 years	0.367***	0.366***	0.360***
	(0.0889)	(0.0890)	(0.0894)
Age: 55 to 64 years	-0.232**	-0.198*	-0.204*
	(0.107)	(0.110)	(0.110)
Age: 65 years and up	-0.376***	-0.233*	-0.292**
	(0.117)	(0.132)	(0.134)
Region: Northeast	0.162**	0.180**	0.162**
	(0.0734)	(0.0732)	(0.0735)
Region: Midwest	-0.0204	-0.0222	-0.0212
	(0.0751)	(0.0750)	(0.0752)
Region: South	0.0522	0.0478	0.0520
	(0.0656)	(0.0656)	(0.0658)
Education: High school	-0.0723		-0.0377
	(0.0702)		(0.0723)
Education: Some college	-0.143**		-0.130**
	(0.0651)		(0.0658)
Education: Masters degree	0.271***		0.269***
	(0.0813)		(0.0814)
Education: Doctoral degree	0.170		0.170

Continued on next page

Table A13 – continued from previous page

	(0.122)		(0.122)
Empl. status: Part time		0.00313	0.0336
		(0.0732)	(0.0740)
Empl. status: Looking for work		-0.219**	-0.183*
		(0.106)	(0.107)
Empl. status: Unemployed		-0.162**	-0.120
		(0.0760)	(0.0782)
Empl. status: Retired		-0.184*	-0.154
		(0.105)	(0.106)
/			
cut1	1.311***	1.285***	1.292***
	(0.101)	(0.0934)	(0.101)
cut2	1.926***	1.896***	1.908***
	(0.104)	(0.0971)	(0.105)
cut3	2.289***	2.254***	2.271***
	(0.108)	(0.100)	(0.108)
cut4	2.719***	2.679***	2.703***
	(0.112)	(0.105)	(0.113)
cut5	3.368***	3.322***	3.354***
	(0.121)	(0.114)	(0.122)
Observations	4161	4161	4161
Max. log-likelihood	-2394.41	-2403.62	-2390.64

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A14: qBus sample: Model 28-30 (of 30) to accommodate eBird missing values

	Model 28	Model 29	Model 30
Engagement-level indicator			
Travel 1+ mile data available	0.192	0.148	0.174
	(0.667)	(0.658)	(0.671)
Trips 1+ miles = 0	-0.929	-0.882	-0.912
	(0.673)	(0.664)	(0.677)
Trips 1+ miles = [1,4)	-0.318	-0.269	-0.301
	(0.684)	(0.675)	(0.688)
Trips 1+ miles = [4,7)	-0.579	-0.553	-0.576
	(0.688)	(0.680)	(0.693)
Trips 1+ miles = [7,10)	-0.406	-0.376	-0.414
	(0.687)	(0.678)	(0.691)
Trips 1+ miles = [10,21)	-0.0974	-0.0572	-0.0898
	(0.673)	(0.664)	(0.677)
Trips 1+ miles = [21,41)	-0.0826	-0.0376	-0.0588
	(0.674)	(0.665)	(0.678)
Trips 1+ miles = [41,72)	0.250	0.279	0.263
	(0.671)	(0.662)	(0.675)
Trips 1+ miles = [72,124)	0.455	0.510	0.470
	(0.669)	(0.660)	(0.673)
Trips 1+ miles = [124,174)	0.352	0.390	0.367
	(0.669)	(0.660)	(0.673)
Trips 1+ miles = [174,238)	0.443	0.472	0.463
	(0.668)	(0.659)	(0.672)
Trips 1+ miles = [238,364)	0.700	0.715	0.718
	(0.667)	(0.658)	(0.671)
Trips 1+ miles = 365	0.667	0.707	0.665
	(0.693)	(0.685)	(0.697)

Continued on next page

Table A14 – continued from previous page

Has participated in CBC	1.947***	1.923***	1.937***
	(0.0700)	(0.0703)	(0.0703)
Hunts birds	0.0422	0.0595	0.0497
	(0.0961)	(0.0963)	(0.0963)
Gender: Female	-0.189***	-0.178***	-0.178***
	(0.0499)	(0.0502)	(0.0506)
Age: 24 years or less	0.523***	0.547***	0.521***
	(0.0960)	(0.0966)	(0.0987)
Age: 25 to 34 years	0.566***	0.556***	0.554***
	(0.0858)	(0.0863)	(0.0867)
Age: 35 to 44 years	0.372***	0.367***	0.365***
	(0.0885)	(0.0889)	(0.0890)
Age: 55 to 64 years	-0.237**	-0.235**	-0.208*
	(0.107)	(0.107)	(0.110)
Age: 65 years and up	-0.334***	-0.379***	-0.253*
	(0.115)	(0.117)	(0.132)
Income: Less than 25K	-0.103	-0.0873	-0.0628
	(0.0809)	(0.0829)	(0.0839)
Income: 25 K to 50 K	-0.0368	-0.0224	-0.0296
	(0.0768)	(0.0771)	(0.0771)
Income: 75 K to 100 K	0.00562	-0.0399	0.000688
	(0.0858)	(0.0866)	(0.0859)
Income: 100 K or more	0.0929	-0.00666	0.0838
	(0.0746)	(0.0782)	(0.0748)
Region: Northeast	0.184**	0.166**	0.182**
	(0.0732)	(0.0736)	(0.0734)
Region: Midwest	-0.0215	-0.0177	-0.0234
	(0.0751)	(0.0753)	(0.0752)
Region: South	0.0557	0.0566	0.0525

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Table A14 – continued from previous page

	(0.0656)	(0.0658)	(0.0658)
Education: High school		-0.0511	
		(0.0745)	
Education: Some college		-0.134**	
		(0.0668)	
Education: Masters degree		0.270***	
		(0.0825)	
Education: Doctoral degree		0.162	
		(0.124)	
Empl. status: Part time			0.0268
			(0.0748)
Empl. status: Looking for work			-0.188*
			(0.108)
Empl. status: Unemployed			-0.129
			(0.0795)
Empl. status: Retired			-0.155
			(0.106)
/			
cut1	1.345***	1.299***	1.313***
	(0.104)	(0.112)	(0.105)
cut2	1.956***	1.914***	1.925***
	(0.107)	(0.115)	(0.108)
cut3	2.315***	2.277***	2.284***
	(0.110)	(0.118)	(0.111)
cut4	2.740***	2.708***	2.711***
	(0.115)	(0.123)	(0.116)
cut5	3.383***	3.357***	3.356***
	(0.124)	(0.132)	(0.125)
Observations	4161	4161	4161
Max. log-likelihood	-2405.49	-2393.71	-2401.66

Continued on next page

Table A14 – continued from previous page

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

G Four-level ordered-probit eBird engagement-level models for all relevant subsets of regressors (using data from the eBird sample)

Table A15: eBird sample: Model 1-3 (of 30) to accommodate missing values

	Model 1	Model 2	Model 3
Engagement-level indicator			
Has participated in CBC	0.487***	0.556***	0.525***
	(0.0678)	(0.0744)	(0.0759)
Hunts birds	0.0400	-0.0868	-0.0443
	(0.128)	(0.139)	(0.140)
Empl. status: Part time		-0.255*	-0.210
		(0.140)	(0.143)
Empl. status: Looking for work		-0.587	-0.562
		(0.425)	(0.428)
Empl. status: Unemployed		-0.154	-0.0841
		(0.157)	(0.161)
Empl. status: Retired		-0.501***	-0.480***
		(0.0807)	(0.0820)
Education: High school			0.197
			(0.219)
Education: Some college			-0.183
			(0.120)
Education: Masters degree			0.0652
			(0.0905)
Education: Doctoral degree			0.266**
			(0.125)
/			
cut1	-0.0249	-0.294***	-0.258***
	(0.0527)	(0.0759)	(0.0967)
cut2	0.715***	0.482***	0.527***

Continued on next page

Table A15 – continued from previous page

	(0.0552)	(0.0762)	(0.0972)
cut3	1.320***	1.086***	1.131***
	(0.0623)	(0.0818)	(0.102)
Observations	1081	918	899
Max. log-likelihood	-1396.30	-1162.68	-1135.31

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A16: eBird sample: Model 4-6 (of 30) to accommodate missing values

	Model 4	Model 5	Model 6
Engagement-level indicator			
Has participated in CBC	0.567***	0.413***	0.522***
	(0.0769)	(0.0700)	(0.0749)
Hunts birds	-0.0758	-0.0716	-0.214
	(0.142)	(0.131)	(0.141)
Age: 24 years or less	0.963***		
	(0.352)		
Age: 25 to 34 years	0.439**		
	(0.172)		
Age: 35 to 44 years	0.330**		
	(0.157)		
Age: 55 to 64 years	-0.140		
	(0.125)		
Age: 65 years and up	-0.163		
	(0.152)		
Empl. status: Part time	-0.222		-0.181
	(0.147)		(0.141)
Empl. status: Looking for work	-0.693		-0.520
	(0.435)		(0.425)
Empl. status: Unemployed	-0.0923		-0.0523
	(0.164)		(0.159)
Empl. status: Retired	-0.260**		-0.469***
	(0.121)		(0.0812)
Education: High school	0.0937	0.102	
	(0.234)	(0.194)	
Education: Some college	-0.135	-0.159	
	(0.122)	(0.108)	
Education: Masters degree	0.126	0.0479	

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Table A16 – continued from previous page

	(0.0919)	(0.0833)	
Education: Doctoral degree	0.344***	0.227*	
	(0.127)	(0.116)	
Gender: Female		-0.357***	-0.373***
		(0.0717)	(0.0771)
/			
cut1	-0.141	-0.268***	-0.518***
	(0.126)	(0.0930)	(0.0889)
cut2	0.666***	0.498***	0.272***
	(0.127)	(0.0934)	(0.0879)
cut3	1.276***	1.113***	0.889***
	(0.131)	(0.0968)	(0.0918)
Observations	898	1053	916
Max. log-likelihood	-1121.46	-1344.47	-1149.42

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A17: eBird sample: Model 7-9 (of 30) to accommodate missing values

	Model 7	Model 8	Model 9
Engagement-level indicator			
Has participated in CBC	0.493***	0.534***	0.500***
	(0.0765)	(0.0700)	(0.0715)
Hunts birds	-0.168	-0.208	-0.162
	(0.143)	(0.133)	(0.133)
Gender: Female	-0.344***	-0.412***	-0.378***
	(0.0787)	(0.0706)	(0.0724)
Empl. status: Part time	-0.144		
	(0.144)		
Empl. status: Looking for work	-0.503		
	(0.427)		
Empl. status: Unemployed	0.0109		
	(0.163)		
Empl. status: Retired	-0.452***		
	(0.0824)		
Education: High school	0.115		0.00592
	(0.220)		(0.207)
Education: Some college	-0.200*		-0.129
	(0.121)		(0.110)
Education: Masters degree	0.0603		0.166*
	(0.0908)		(0.0852)
Education: Doctoral degree	0.198		0.336***
	(0.126)		(0.118)
Age: 24 years or less		0.632**	0.769***
		(0.255)	(0.268)
Age: 25 to 34 years		0.328**	0.389**
		(0.155)	(0.157)
Age: 35 to 44 years		0.172	0.187

Continued on next page

Table A17 – continued from previous page

		(0.141)	(0.142)
Age: 55 to 64 years		-0.305***	-0.306***
		(0.107)	(0.108)
Age: 65 years and up		-0.431***	-0.439***
		(0.105)	(0.106)
/			
cut1	-0.480***	-0.490***	-0.394***
	(0.110)	(0.107)	(0.124)
cut2	0.317***	0.305***	0.413***
	(0.109)	(0.106)	(0.124)
cut3	0.931***	0.939***	1.046***
	(0.112)	(0.109)	(0.127)
Observations	897	1071	1051
Max. log-likelihood	-1124.29	-1339.49	-1307.49

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A18: eBird sample: Model 10-12 (of 30) to accommodate missing values

	Model 10	Model 11	Model 12
Engagement-level indicator			
Has participated in CBC	0.568***	0.535***	0.491***
	(0.0761)	(0.0775)	(0.0795)
Hunts birds	-0.259*	-0.207	-0.186
	(0.143)	(0.144)	(0.140)
Gender: Female	-0.385***	-0.359***	-0.364***
	(0.0779)	(0.0796)	(0.0804)
Age: 24 years or less	0.875***	0.924***	0.789**
	(0.334)	(0.352)	(0.315)
Age: 25 to 34 years	0.391**	0.424**	0.317*
	(0.171)	(0.173)	(0.167)
Age: 35 to 44 years	0.317**	0.321**	0.125
	(0.156)	(0.157)	(0.151)
Age: 55 to 64 years	-0.154	-0.161	-0.376***
	(0.124)	(0.126)	(0.117)
Age: 65 years and up	-0.217	-0.232	-0.405***
	(0.151)	(0.154)	(0.118)
Empl. status: Part time	-0.180	-0.136	
	(0.147)	(0.149)	
Empl. status: Looking for work	-0.663	-0.635	
	(0.433)	(0.435)	
Empl. status: Unemployed	-0.0534	0.00968	
	(0.163)	(0.165)	
Empl. status: Retired	-0.222*	-0.188	
	(0.120)	(0.123)	
Education: High school		0.0161	0.145
		(0.235)	(0.237)
Education: Some college		-0.149	-0.135

Continued on next page

Table A18 – continued from previous page

		(0.122)	(0.122)
Education: Masters degree		0.125	0.108
		(0.0922)	(0.0943)
Education: Doctoral degree		0.279**	0.251*
		(0.128)	(0.133)
Income: Less than 25K			-0.133
			(0.170)
Income: 25 K to 50 K			0.118
			(0.117)
Income: 75 K to 100 K			-0.127
			(0.122)
Income: 100 K or more			0.117
			(0.106)
/			
cut1	-0.464***	-0.383***	-0.478***
	(0.119)	(0.137)	(0.154)
cut2	0.347***	0.438***	0.378**
	(0.118)	(0.137)	(0.154)
cut3	0.972***	1.059***	1.017***
	(0.122)	(0.140)	(0.156)
Observations	914	896	853
Max. log-likelihood	-1134.81	-1109.77	-1076.62

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A19: eBird sample: Model 13-15 (of 30) to accommodate missing values

	Model 13	Model 14	Model 15
Engagement-level indicator			
Has participated in CBC	0.562***	0.534***	0.0305
	(0.0846)	(0.0867)	(0.0844)
Hunts birds	-0.290*	-0.241	0.106
	(0.148)	(0.150)	(0.152)
Gender: Female	-0.387***	-0.375***	
	(0.0867)	(0.0888)	
Age: 24 years or less	1.021***	0.986**	
	(0.396)	(0.403)	
Age: 25 to 34 years	0.341*	0.330*	
	(0.185)	(0.188)	
Age: 35 to 44 years	0.233	0.229	
	(0.167)	(0.168)	
Age: 55 to 64 years	-0.195	-0.217	
	(0.134)	(0.136)	
Age: 65 years and up	-0.103	-0.125	
	(0.167)	(0.170)	
Income: Less than 25K	-0.267	-0.198	
	(0.193)	(0.200)	
Income: 25 K to 50 K	0.0989	0.150	
	(0.124)	(0.127)	
Income: 75 K to 100 K	-0.204	-0.182	
	(0.131)	(0.132)	
Income: 100 K or more	0.0531	0.0303	
	(0.115)	(0.117)	
Empl. status: Part time	-0.181	-0.164	
	(0.160)	(0.161)	
Empl. status: Looking for work	-0.476	-0.482	

Continued on next page

Table A19 – continued from previous page

	(0.462)	(0.465)	
Empl. status: Unemployed	-0.163	-0.127	
	(0.188)	(0.190)	
Empl. status: Retired	-0.343**	-0.321**	
	(0.135)	(0.136)	
Education: High school		0.130	
		(0.259)	
Education: Some college		-0.142	
		(0.138)	
Education: Masters degree		0.0764	
		(0.102)	
Education: Doctoral degree		0.196	
		(0.144)	
Travel 1+ mile data available			0
			(.)
Trips 1+ miles = 0			-2.765***
			(0.187)
Trips 1+ miles = [1,4)			-2.923***
			(0.213)
Trips 1+ miles = [4,7)			-1.944***
			(0.222)
Trips 1+ miles = [7,10)			-1.587***
			(0.283)
Trips 1+ miles = [10,21)			-1.556***
			(0.202)
Trips 1+ miles = [21,41)			-1.371***
			(0.216)
Trips 1+ miles = [41,72)			-1.097***

Continued on next page

Table A19 – continued from previous page

			(0.207)
Trips 1+ miles = [72,124)			-0.695***
			(0.213)
Trips 1+ miles = [124,174)			-0.560**
			(0.231)
Trips 1+ miles = [174,238)			-0.426
			(0.265)
Trips 1+ miles = [238,364)			-0.399*
			(0.229)
Trips 1+ miles = 365			0
			(.)
/			
cut1	-0.599***	-0.555***	-2.506***
	(0.156)	(0.174)	(0.187)
cut2	0.285*	0.335*	-1.346***
	(0.156)	(0.173)	(0.178)
cut3	0.908***	0.954***	-0.401**
	(0.159)	(0.176)	(0.173)
Observations	740	727	831
Max. log-likelihood	-924.96	-907.59	-875.39

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A20: eBird sample: Model 16-18 (of 30) to accommodate missing values

	Model 16	Model 17	Model 18
Engagement-level indicator			
Travel 1+ mile data available	0	0	0
	(.)	(.)	(.)
Trips 1+ miles = 0	-2.761***	-2.837***	-2.855***
	(0.190)	(0.211)	(0.208)
Trips 1+ miles = [1,4)	-2.983***	-3.107***	-3.090***
	(0.218)	(0.242)	(0.240)
Trips 1+ miles = [4,7)	-1.977***	-1.959***	-1.955***
	(0.226)	(0.258)	(0.255)
Trips 1+ miles = [7,10)	-1.698***	-1.993***	-1.896***
	(0.290)	(0.314)	(0.309)
Trips 1+ miles = [10,21)	-1.546***	-1.678***	-1.692***
	(0.205)	(0.226)	(0.224)
Trips 1+ miles = [21,41)	-1.368***	-1.439***	-1.453***
	(0.219)	(0.240)	(0.237)
Trips 1+ miles = [41,72)	-1.105***	-1.196***	-1.225***
	(0.209)	(0.232)	(0.232)
Trips 1+ miles = [72,124)	-0.678***	-0.629***	-0.676***
	(0.216)	(0.238)	(0.236)
Trips 1+ miles = [124,174)	-0.592**	-0.629**	-0.622**
	(0.235)	(0.264)	(0.261)
Trips 1+ miles = [174,238)	-0.404	-0.546*	-0.568**
	(0.272)	(0.291)	(0.284)
Trips 1+ miles = [238,364)	-0.410*	-0.522**	-0.551**
	(0.234)	(0.258)	(0.255)
Trips 1+ miles = 365	0	0	0
	(.)	(.)	(.)
Has participated in CBC	0.0272	0.125	0.160*

Continued on next page

Table A20 – continued from previous page

	(0.0859)	(0.0935)	(0.0936)
Hunts birds	0.108	0.00874	-0.00447
	(0.153)	(0.170)	(0.170)
Education: High school	0.427*	0.462*	
	(0.235)	(0.255)	
Education: Some college	0.00506	-0.114	
	(0.134)	(0.150)	
Education: Masters degree	0.176*	0.183*	
	(0.0980)	(0.108)	
Education: Doctoral degree	0.147	0.0672	
	(0.133)	(0.144)	
Empl. status: Part time		-0.116	-0.226
		(0.169)	(0.173)
Empl. status: Looking for work		-0.718	-0.976*
		(0.587)	(0.589)
Empl. status: Unemployed		0.0905	0.0520
		(0.186)	(0.185)
Empl. status: Retired		-0.322***	-0.342**
		(0.0976)	(0.142)
Age: 24 years or less			0.755**
			(0.346)
Age: 25 to 34 years			0.206
			(0.194)
Age: 35 to 44 years			0.281
			(0.180)
Age: 55 to 64 years			-0.110
			(0.145)
Age: 65 years and up			0.130
			(0.178)

Continued on next page

Table A20 – continued from previous page

/			
cut1	-2.420***	-2.670***	-2.711***
	(0.202)	(0.231)	(0.235)
cut2	-1.243***	-1.434***	-1.457***
	(0.193)	(0.221)	(0.225)
cut3	-0.303	-0.496**	-0.510**
	(0.188)	(0.215)	(0.220)
Observations	810	693	707
Max. log-likelihood	-850.08	-711.03	-722.39

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A21: eBird sample: Model 19-21 (of 30) to accommodate missing values

	Model 19	Model 20	Model 21
Engagement-level indicator			
Travel 1+ mile data available	0	0	0
	(.)	(.)	(.)
Trips 1+ miles = 0	-2.867***	-2.810***	-2.850***
	(0.212)	(0.207)	(0.228)
Trips 1+ miles = [1,4)	-3.151***	-3.071***	-3.140***
	(0.245)	(0.242)	(0.267)
Trips 1+ miles = [4,7)	-2.024***	-2.120***	-1.884***
	(0.259)	(0.250)	(0.286)
Trips 1+ miles = [7,10)	-2.086***	-2.084***	-2.285***
	(0.318)	(0.346)	(0.370)
Trips 1+ miles = [10,21)	-1.707***	-1.800***	-1.851***
	(0.227)	(0.226)	(0.249)
Trips 1+ miles = [21,41)	-1.484***	-1.494***	-1.520***
	(0.241)	(0.238)	(0.261)
Trips 1+ miles = [41,72)	-1.247***	-1.341***	-1.363***
	(0.234)	(0.227)	(0.253)
Trips 1+ miles = [72,124)	-0.675***	-0.844***	-0.728***
	(0.239)	(0.233)	(0.258)
Trips 1+ miles = [124,174)	-0.677**	-0.696***	-0.654**
	(0.265)	(0.258)	(0.292)
Trips 1+ miles = [174,238)	-0.565*	-0.465	-0.569*
	(0.292)	(0.298)	(0.321)
Trips 1+ miles = [238,364)	-0.575**	-0.396	-0.424
	(0.260)	(0.260)	(0.286)
Trips 1+ miles = 365	0	0	0
	(.)	(.)	(.)
Has participated in CBC	0.150	0.103	0.183*

Continued on next page

Table A21 – continued from previous page

	(0.0948)	(0.0972)	(0.106)
Hunts birds	-0.0170	0.0233	-0.0400
	(0.171)	(0.164)	(0.177)
Age: 24 years or less	0.640*	0.902***	1.019**
	(0.370)	(0.334)	(0.423)
Age: 25 to 34 years	0.267	0.208	0.298
	(0.196)	(0.191)	(0.215)
Age: 35 to 44 years	0.301*	0.308*	0.325*
	(0.181)	(0.174)	(0.192)
Age: 55 to 64 years	-0.128	-0.300**	-0.117
	(0.148)	(0.137)	(0.159)
Age: 65 years and up	0.102	-0.184	0.161
	(0.181)	(0.137)	(0.200)
Empl. status: Part time	-0.189		-0.169
	(0.175)		(0.187)
Empl. status: Looking for work	-0.908		-0.825
	(0.593)		(0.650)
Empl. status: Unemployed	0.0780		-0.0457
	(0.189)		(0.214)
Empl. status: Retired	-0.307**		-0.343**
	(0.145)		(0.162)
Education: High school	0.392	0.606**	0.718**
	(0.275)	(0.280)	(0.308)
Education: Some college	-0.0874	0.0891	0.00245
	(0.152)	(0.150)	(0.169)
Education: Masters degree	0.222**	0.305***	0.259**
	(0.110)	(0.110)	(0.121)
Education: Doctoral degree	0.116	0.160	0.0245

Continued on next page

Table A21 – continued from previous page

	(0.147)	(0.150)	(0.164)
Income: Less than 25K		0.0219	-0.0785
		(0.209)	(0.254)
Income: 25 K to 50 K		0.154	0.154
		(0.138)	(0.150)
Income: 75 K to 100 K		0.0584	0.00504
		(0.144)	(0.157)
Income: 100 K or more		0.240*	0.167
		(0.123)	(0.136)
/			
cut1	-2.632***	-2.483***	-2.586***
	(0.250)	(0.249)	(0.282)
cut2	-1.370***	-1.211***	-1.246***
	(0.240)	(0.241)	(0.273)
cut3	-0.425*	-0.241	-0.302
	(0.236)	(0.236)	(0.268)
Observations	692	674	573
Max. log-likelihood	-704.13	-697.49	-583.38

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A22: eBird sample: Model 22-24 (of 30) to accommodate missing values

	Model 22	Model 23	Model 24
Engagement-level indicator			
Travel 1+ mile data available	0	0	0
	(.)	(.)	(.)
Trips 1+ miles = 0	-2.735***	-2.732***	-2.810***
	(0.188)	(0.191)	(0.211)
Trips 1+ miles = [1,4)	-2.886***	-2.952***	-3.082***
	(0.214)	(0.219)	(0.243)
Trips 1+ miles = [4,7)	-1.922***	-1.956***	-1.933***
	(0.223)	(0.226)	(0.258)
Trips 1+ miles = [7,10)	-1.545***	-1.659***	-1.948***
	(0.284)	(0.291)	(0.315)
Trips 1+ miles = [10,21)	-1.514***	-1.512***	-1.650***
	(0.203)	(0.206)	(0.227)
Trips 1+ miles = [21,41)	-1.334***	-1.341***	-1.416***
	(0.217)	(0.220)	(0.240)
Trips 1+ miles = [41,72)	-1.089***	-1.098***	-1.189***
	(0.206)	(0.209)	(0.232)
Trips 1+ miles = [72,124)	-0.668***	-0.658***	-0.611**
	(0.213)	(0.216)	(0.238)
Trips 1+ miles = [124,174)	-0.551**	-0.581**	-0.623**
	(0.231)	(0.235)	(0.265)
Trips 1+ miles = [174,238)	-0.429	-0.411	-0.563*
	(0.265)	(0.272)	(0.291)
Trips 1+ miles = [238,364)	-0.394*	-0.410*	-0.518**
	(0.229)	(0.234)	(0.258)
Trips 1+ miles = 365	0	0	0
	(.)	(.)	(.)
Has participated in CBC	0.0210	0.0183	0.115

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Table A22 – continued from previous page

	(0.0848)	(0.0862)	(0.0939)
Hunts birds	0.0512	0.0583	-0.0406
	(0.155)	(0.156)	(0.172)
Gender: Female	-0.160*	-0.132	-0.148
	(0.0830)	(0.0855)	(0.0940)
Education: High school		0.404*	0.437*
		(0.235)	(0.255)
Education: Some college		0.00943	-0.114
		(0.134)	(0.151)
Education: Masters degree		0.174*	0.183*
		(0.0981)	(0.108)
Education: Doctoral degree		0.115	0.0368
		(0.135)	(0.146)
Empl. status: Part time			-0.0868
			(0.170)
Empl. status: Looking for work			-0.716
			(0.584)
Empl. status: Unemployed			0.135
			(0.188)
Empl. status: Retired			-0.305***
			(0.0980)
/			
cut1	-2.587***	-2.490***	-2.738***
	(0.192)	(0.207)	(0.236)
cut2	-1.415***	-1.309***	-1.498***
	(0.182)	(0.198)	(0.225)
cut3	-0.466***	-0.365*	-0.557**
	(0.176)	(0.193)	(0.220)
Observations	826	808	691
Max. log-likelihood	-868.79	-847.83	-708.91

Continued on next page

Table A22 – continued from previous page

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A23: eBird sample: Model 25-27 (of 30) to accommodate missing values

	Model 25	Model 26	Model 27
Engagement-level indicator			
Travel 1+ mile data available	0	0	0
	(.)	(.)	(.)
Trips 1+ miles = 0	-2.750***	-2.820***	-2.838***
	(0.192)	(0.209)	(0.212)
Trips 1+ miles = [1,4)	-2.969***	-3.053***	-3.123***
	(0.221)	(0.241)	(0.245)
Trips 1+ miles = [4,7)	-2.031***	-1.928***	-1.997***
	(0.227)	(0.255)	(0.260)
Trips 1+ miles = [7,10)	-1.786***	-1.850***	-2.041***
	(0.294)	(0.310)	(0.320)
Trips 1+ miles = [10,21)	-1.559***	-1.658***	-1.678***
	(0.207)	(0.224)	(0.228)
Trips 1+ miles = [21,41)	-1.378***	-1.419***	-1.459***
	(0.221)	(0.238)	(0.241)
Trips 1+ miles = [41,72)	-1.157***	-1.210***	-1.235***
	(0.210)	(0.232)	(0.234)
Trips 1+ miles = [72,124)	-0.693***	-0.652***	-0.656***
	(0.216)	(0.236)	(0.239)
Trips 1+ miles = [124,174)	-0.612***	-0.617**	-0.669**
	(0.236)	(0.261)	(0.265)
Trips 1+ miles = [174,238)	-0.413	-0.573**	-0.578**
	(0.272)	(0.284)	(0.291)
Trips 1+ miles = [238,364)	-0.456*	-0.536**	-0.567**
	(0.235)	(0.255)	(0.260)
Trips 1+ miles = 365	0	0	0
	(.)	(.)	(.)
Has participated in CBC	0.0882	0.150	0.142

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Table A23 – continued from previous page

	(0.0880)	(0.0939)	(0.0952)
Hunts birds	-0.00231	-0.0533	-0.0639
	(0.158)	(0.173)	(0.174)
Gender: Female	-0.136	-0.154*	-0.138
	(0.0862)	(0.0927)	(0.0951)
Age: 24 years or less	0.649**	0.737**	0.628*
	(0.288)	(0.346)	(0.370)
Age: 25 to 34 years	0.194	0.216	0.271
	(0.178)	(0.194)	(0.197)
Age: 35 to 44 years	0.279*	0.288	0.304*
	(0.165)	(0.180)	(0.181)
Age: 55 to 64 years	-0.268**	-0.110	-0.131
	(0.127)	(0.145)	(0.148)
Age: 65 years and up	-0.223*	0.109	0.0808
	(0.124)	(0.179)	(0.182)
Education: High school	0.323		0.374
	(0.250)		(0.275)
Education: Some college	0.0255		-0.0841
	(0.137)		(0.152)
Education: Masters degree	0.269***		0.224**
	(0.101)		(0.110)
Education: Doctoral degree	0.203		0.0900
	(0.137)		(0.148)
Empl. status: Part time		-0.189	-0.156
		(0.175)	(0.177)
Empl. status: Looking for work		-0.978*	-0.908
		(0.587)	(0.590)
Empl. status: Unemployed		0.103	0.121

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Table A23 – continued from previous page

		(0.188)	(0.191)
Empl. status: Retired		-0.308**	-0.276*
		(0.144)	(0.147)
/			
cut1	-2.567***	-2.768***	-2.691***
	(0.227)	(0.238)	(0.254)
cut2	-1.345***	-1.510***	-1.425***
	(0.218)	(0.227)	(0.244)
cut3	-0.388*	-0.558**	-0.476**
	(0.213)	(0.222)	(0.239)
Observations	807	705	690
Max. log-likelihood	-833.29	-720.01	-702.08

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A24: eBird sample: Model 28-30 (of 30) to accommodate missing values

	Model 28	Model 29	Model 30
Engagement-level indicator			
Travel 1+ mile data available	0	0	0
	(.)	(.)	(.)
Trips 1+ miles = 0	-2.757***	-2.791***	-2.767***
	(0.204)	(0.208)	(0.224)
Trips 1+ miles = [1,4)	-2.928***	-3.047***	-3.002***
	(0.237)	(0.244)	(0.262)
Trips 1+ miles = [4,7)	-2.043***	-2.105***	-1.773***
	(0.246)	(0.251)	(0.281)
Trips 1+ miles = [7,10)	-1.792***	-2.052***	-1.943***
	(0.335)	(0.349)	(0.356)
Trips 1+ miles = [10,21)	-1.751***	-1.774***	-1.777***
	(0.226)	(0.229)	(0.247)
Trips 1+ miles = [21,41)	-1.450***	-1.475***	-1.450***
	(0.235)	(0.240)	(0.257)
Trips 1+ miles = [41,72)	-1.312***	-1.335***	-1.317***
	(0.224)	(0.227)	(0.251)
Trips 1+ miles = [72,124)	-0.841***	-0.830***	-0.714***
	(0.230)	(0.233)	(0.255)
Trips 1+ miles = [124,174)	-0.670***	-0.685***	-0.609**
	(0.253)	(0.258)	(0.287)
Trips 1+ miles = [174,238)	-0.466	-0.467	-0.540*
	(0.294)	(0.298)	(0.316)
Trips 1+ miles = [238,364)	-0.396	-0.392	-0.418
	(0.255)	(0.260)	(0.279)
Trips 1+ miles = 365	0	0	0
	(.)	(.)	(.)
Has participated in CBC	0.0778	0.0956	0.160

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Table A24 – continued from previous page

	(0.0954)	(0.0975)	(0.104)
Hunts birds	0.00672	-0.00191	-0.0502
	(0.166)	(0.167)	(0.179)
Gender: Female	-0.110	-0.0712	-0.125
	(0.0936)	(0.0965)	(0.104)
Age: 24 years or less	0.909***	0.893***	1.144***
	(0.324)	(0.334)	(0.413)
Age: 25 to 34 years	0.119	0.207	0.218
	(0.188)	(0.191)	(0.212)
Age: 35 to 44 years	0.249	0.307*	0.284
	(0.172)	(0.174)	(0.190)
Age: 55 to 64 years	-0.267**	-0.298**	-0.0908
	(0.134)	(0.137)	(0.156)
Age: 65 years and up	-0.170	-0.186	0.188
	(0.135)	(0.137)	(0.197)
Income: Less than 25K	-0.0147	0.0242	-0.128
	(0.200)	(0.209)	(0.240)
Income: 25 K to 50 K	0.113	0.146	0.135
	(0.134)	(0.138)	(0.145)
Income: 75 K to 100 K	0.0129	0.0453	-0.0415
	(0.143)	(0.145)	(0.156)
Income: 100 K or more	0.191	0.225*	0.116
	(0.121)	(0.124)	(0.134)
Education: High school		0.590**	
		(0.281)	
Education: Some college		0.0934	
		(0.151)	
Education: Masters degree		0.303***	

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Table A24 – continued from previous page

		(0.111)	
Education: Doctoral degree		0.146	
		(0.151)	
Empl. status: Part time			-0.162
			(0.187)
Empl. status: Looking for work			-0.861
			(0.646)
Empl. status: Unemployed			-0.00203
			(0.213)
Empl. status: Retired			-0.369**
			(0.160)
/			
cut1	-2.706***	-2.525***	-2.749***
	(0.240)	(0.255)	(0.272)
cut2	-1.457***	-1.252***	-1.424***
	(0.230)	(0.246)	(0.262)
cut3	-0.488**	-0.281	-0.483*
	(0.225)	(0.241)	(0.257)
Observations	687	673	584
Max. log-likelihood	-718.20	-696.80	-599.55

t in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

H Heterogeneous population weights for eBird sample

Selection-correction models allow the analyst to accommodate the possibility that there is a correlation between the *unobserved error term* in the process that leads to an individual's presence in the estimating sample and the *unobserved error term* in the process that generates the outcome variable for that individual. However, it is possible that the *observable heterogeneity* across the individuals who show up in the estimating sample could also be different from the observable heterogeneity in the general population.

In such a case, researchers often consider the use of exogenous weights. Weights are used to scale the relative frequency of people of different types in the estimating sample so that group proportions more closely match the corresponding group proportions in the population. With a fully representative estimating sample, each observation represents an equal number of people in the population as a whole, so that average preferences in the sample (for example) should be the same as average preferences in the population. If each observation in the sample represents a very different number of people in the population, then estimated average preferences are less likely to scale up to the general population.

We seek an appropriate set of weights to use when estimating our outcome equation, to explain consideration-set radius (i.e. the maximum one-way distance a respondent is willing to travel on a day-trip to see wild birds). Many weighting schemes employ the relative frequencies of people of different types in the population divided by the relative frequencies of people of those same types in the estimating sample. The ratios of relative frequencies are then scaled so that they sum to the size of the estimating sample. Typically, the researchers bins both the population and the estimating sample according to the values of some set of exogenous variables.

For rudimentary weights, we could use the observed undifferentiated proportions of respondents at each engagement level in the two samples, (qBus, eBird) = (0.273, 0.398), (0.252, 0.275), (0.265, 0.179), and (0.210, 0.146). However, we are also concerned that engagement intensity is not fully exogenous to the maximum distance variable we seek to model. Observed proportions do not allow for the possibility of systematically different mixes of people in the two samples. Thus we adapt the conventional exogenous weighting approach to express the *fitted probabilities* of an individual from each sample exhibiting the engagement intensity that they report. We compute our weights based on the within-sample fitted probabilities that each respondent participated in eBird at each of the four possible engagement levels, where these fitted probabilities are expressed as functions of the individual's exogenous characteristics, and any error term in the fitted probabilities is implicitly discarded, making each fitted probability a function of exogenous variables only.

For our eBird data, we are concerned that (a) the relative *proportions* of respondents in our eBird sample who engage with the project at different levels might differ from (b) the corresponding proportions in the population of eBird members who turn up in a random sample from the general population (i.e. our qBus sample). We again transfer our qBus parameter estimates for the six-level ordered-probit models with the sociodemographic characteristics of each person in our eBird member survey sample to calculate the *predicted* individual conditional engagement-level *probabilities* for respondents in our eBird member

survey sample, as are shown in panel C of Figure 1 in the body of the paper (or Figure A1 in these supplementary materials). But then we also use our eBird member survey sample, *independently*, to estimate four-level ordered-probit models for engagement levels 3, 4, 5 and 6, and calculate predicted probabilities for these four engagement levels based on those parameters, where the distribution of these probabilities is shown in panel B of Figure 1 in the paper. We treat these two sets of predicted probabilities as the "expected" probabilities and the "observed" probabilities in the eBird member survey sample.

We construct our weights for each observation in the eBird sample by considering the observed engagement level for that person. We then generate a weight that reflects (a) the out-of-sample *predicted* probability that a person with these same characteristics would be at that level of engagement in the general population (qBus) sample, in ratio to (b) the within-sample *fitted* probability, estimated using the eBird member survey data, that they are at their observed level of engagement. As usual, we scale these weights so that they sum to the sample size for the eBird member survey. Figure A3 shows the smoothed density for the resulting distribution of heterogeneous weights for use in estimation of the outcome model that uses only the eBird member survey data (with a dotted line highlighting unit weights). For comparison, Figure A3 also shows what would be the four unique values of the set of homogeneous weights that would be calculated if we based the weight calculations only on the marginal distributions of engagement intensities, without reference to the heterogenity in respondent characteristics across the qBus general population sample and the eBird member survey sample.

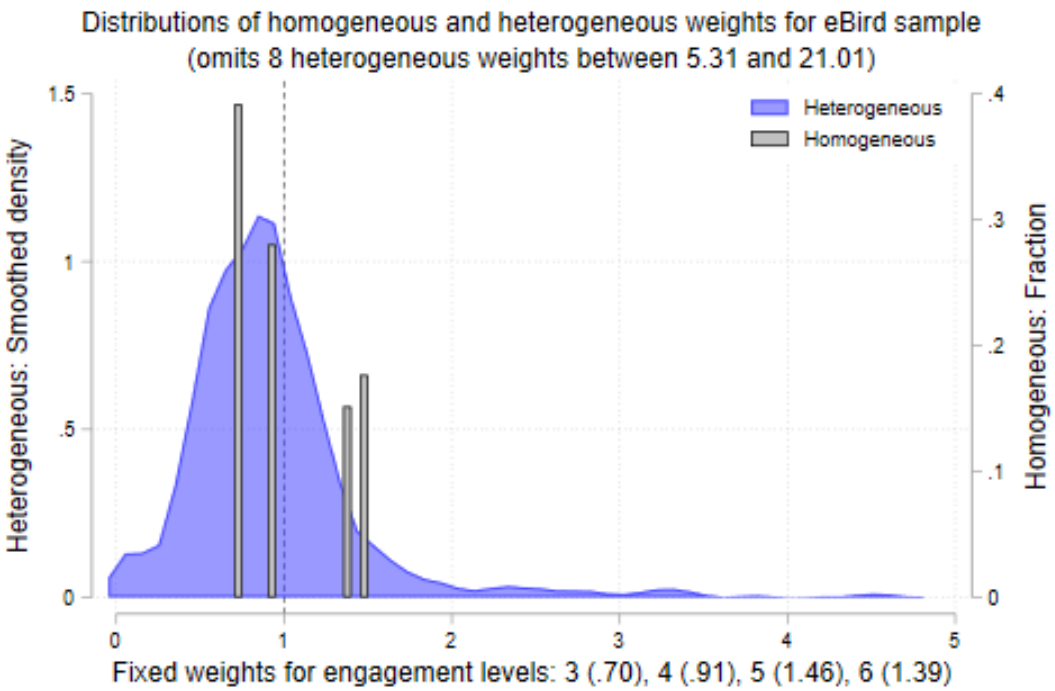

Figure A3: Distribution of weights across eBird member survey observations, where these weights serve to match engagement-intensity probabilities in the eBird member survey sample to engagement-intensity probabilities in the general-population qBus sample (six outlier weights, between 2.66 and 7.93, are not shown)

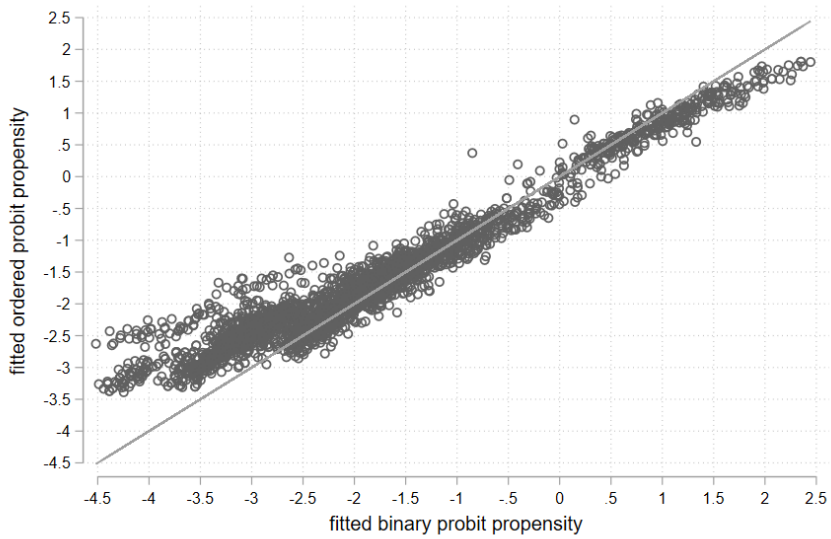

Figure A4: For 4,161 qBus general population respondents only: Fitted engagement propensities calculated from the higher-resolution ordered-probit model plotted against those from the simpler binary-probit model; equal values fall along the line

I Visualization: estimates of intermediate components

For the qBus dataset alone, which includes both members and non-members of eBird, Figure A4 shows the joint distribution of the (adjusted) fitted propensity index, $Z_i\hat{\gamma}^q$, for our new ordered-probit selection equation as well as the fitted propensity index, $Z_i\hat{\gamma}^q$ from a conventional binary-probit selection model using the same qBus data. The propensity index from our new ordered-probit selection model is somewhat higher than the index for the conventional binary model among people with low propensities to belong to eBird, but the upper part of the joint distribution coincides fairly closely. Our ordered-probit selection model recruits more information, with its multiple categories, from both non-members and members of eBird in the qBus sample, which likely accounts for the differences.

We can also consider the differences in the distributions of our two alternative IMR terms, calculated using parameter estimates from the qBus sample, *applied to individuals in our eBird member survey sample*. These two IMR variables are based on our two different selection models: (1) the binary-probit model and (2) the re-normalized (adjusted) ordered-probit model. Figure A5 shows the joint distribution of these two IMR terms.

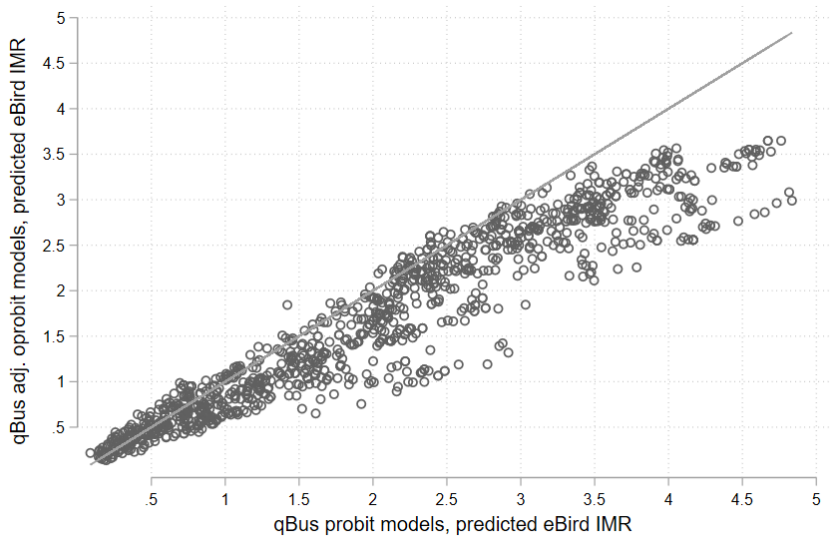

Figure A5: For 1,081 eBird member survey respondents: Predicted ordered-probit-based IMRs calculated with parameters estimated using qBus sample, plotted against predicted binary-probit-based IMRs calculated with parameters estimated using the qBus sample. For each individual observation in the eBird sample, we use the most-detailed qBus specification consistent with missing Z_j data for that observation.

Figure A6 illustrates the high degree of collinearity between the predicted inverse Mills ratio correction term and the predicted engagement propensity for the eBird sample. Had we devoted space in Table 4 to a model with only an interaction term between the demeaned engagement propensity and the intercept term in the model, the coefficient on the single additional would have adapted to the change of scale and sign in the propensity, as opposed to the inverse Mills ratio, and essentially the same values for the remaining parameters would result.

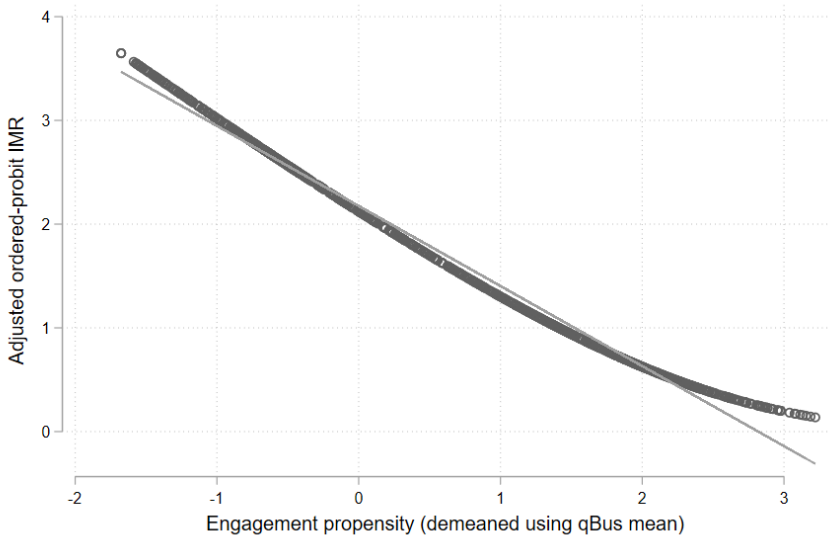

Figure A6: The relationship between our adjusted ordered-probit inverse Mills ratio term used in Model 4 in Table 4 and the underlying demeaned engagement propensity variable used to shift the basic coefficients in Model 5.

J Remaining issues: transfer of selection propensities

J.1 Outcome equation is a conditional logit choice model

Our broader research project with the eBird sample involves destination choice models and inferred preferences for site attributes, employed to estimate non-market benefits associated with wild birds. However, Heckman selection-correction models are not appropriate when the outcome variable of interest is a discrete choice, because the latent choice propensity in a multiple discrete-choice model is *not* conditionally normally distributed.[11] When there is no bivariate normal error term to justify the use of a fitted IMR from a selection model as an additional regressor in an outcome equation, it is nevertheless still possible to explore the more ad hoc correction that accommodates systematic differences in selection propensities across respondents by allowing second-stage parameters to differ systematically with deviations of fitted respondent selection propensities from the average propensity in the general population. This ad hoc correction is used in Cameron and DeShazo (2013), Johnston and Abdulrahman (2017), Kolstoe and Cameron (2017) and Kolstoe et al. (2018). As mentioned in Appendix B, Terza (2009) offers models that hint at the possibility of selection-correction methods for conditional logit models, but his method would need to be adapted extensively to suit the case where the selection model is to be transferred to a different sample.

J.2 Estimated regressors and inference in a second-stage model

Of course, any two-step estimation process that does not account for the estimated property of the $\hat{\gamma}^q$ parameters embodied in the calculated IMR terms—as in Models 3 and 4 (or the fitted de-meaned response propensities, as in Model 5)—can risk some bias in the inferences to be drawn in the second step. The IMR term (or fitted de-meaned predicted response propensity) is an "estimated regressor" that likely overstates the amount of information in the data. It may be straightforward (if tedious), to implement an appropriate FIML estimator in the case where one does not need to contend with any missing data in the dataset to which the selection specification is to be transferred. Recall that in this case, it was necessary to estimate 30 different selection equation specifications using many combinations of none, some, or all of the categories of indicators in the full selection model.

If all variables for the selection equation were available for every observation in the CS sample having the outcome variable of interest, one could define the log-likelihood function over the full set of parameters: $\gamma, \beta, \sigma_\eta, \sigma_\epsilon, \rho$. The structure of the two-step model could be preserved, but the two equations could be estimated simultaneously, constraining the γ parameters to be the same in both the selection equation (using the qBus sample) and the outcome equation (using the IMR term), where the index for the IMR variable is constructed using the γ parameters combined with the Z_j variables for the eBird dataset. The matter of how to construct the weights would need to be resolved, of course. We do not attempt this

[11] Some researchers (e.g. Yuan et al. (2015)) have inserted a fitted inverse Mills ratio (IMR) into a second-stage discrete-choice model, although there seems to be no statistical justification for this particular transformation of the fitted selection propensity.

FIML estimation here, because of the significant amount of missing data for the selection equation applied to the eBird sample, and corresponding proliferation of different specifications necessary to provide predicted propensities, IMRs, and weights that maximize our use of the available data for each eBird respondent. While joint estimation of 30 different ordered-probit equations plus the outcome equations would likely be possible, we would not expect it to make any qualitative difference in our findings.

J.3 Other possible layers of selection

Our estimating sample for the illustrative market-extent model in this paper consists of respondents to our eBird member survey who provided complete data for all except the (typically sensitive) detailed income variable. The selection-correction strategies we feature in this paper presume that this group of eBird member survey respondents is representative of eBird members, an assumption we make to permit us to focus on the problem of systematic selection into eBird engagement at different levels of intensity.

Of course, there may be a variety of reasons why invited eBird members decide not to participate in our survey. In other research, we have sought to control for heterogeneous selection across all eBird members (rather than the general population) by linking the center of gravity of their birding trips to a specific census tract, which we impute to be their home census tract. We have employed census tract attributes as proxies for possible systematic variation across birder characteristics because there is no sociodemographic information available for eBird members who did not respond to our survey. We then employ these various census tract attributes to construct a "propensity of an invited eBird member to respond to our survey" and use this propensity in an attempt to control crudely for selection into our estimating sample for destination choice models. We do not attempt to overlay that correction procedure in addition to the strategies employed here. It is possible that the selection of eBird members into our survey, based on the attributes of their home zipcode relative to those of the general population, is dominated by the selection of the general population into eBird participation, but this is an empirical question that is beyond the scope of this study.

Even with the illustrative example concerning the the radii of consideration sets for birding excursions, it is possible that sample selection may occur along more than one dimension. Respondents to our eBird survey may have unobserved characteristics that make them simultaneously more likely (than otherwise expected) to be members of eBird and also more-likely than average to participate in travel of more than one mile from home to observe birds. In other research, it is this second behavior upon which we base our models of the "active" recreational use of opportunities to watch wild birds. In addition to the eBird engagement-level variable captured by our ordinal variable $CS6_i$, we can also distinguish between birders who do, or do not, travel more than one mile to see birds, in both the qBus sample and the eBird sample. Three categories of actual bird-watching might be distinguished: no birding trips, trips only less than 1 mile, and trips of one mile or more. Thus the ordinal eBird engagement levels might be supplemented by a second (presumably correlated) ordinal variable that captures heterogeneity in the actual bird-watching behavior of respondents in both surveys. Models with selection on two (correlated) latent variables would require working

with trivariate normal joint distributions of the error terms. These models are also beyond the scope of the current paper, again because of the 30 different ordered-probit selection equations necessary to accommodate transfer of our selection model from the qBus sample to the eBird member survey sample with its missing values for different variables.

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