STUDY SERIES
(Statistics #2023-01)

A Comparison of Map Usability via Bivariate Ordinal Analysis

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Report Issued: April 12, 2023

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April 12, 2023

Abstract

Nichols et al. (2023+) present a study where respondents compare usability of two types of geographic maps: satellite maps, which display details such as landmarks and terrain, and simplified road maps. Ordinal responses measured self-reported familiarity with the maps and accuracy in finding a respondent's home and neighboring homes. The present report compares satellite and road maps for each of the two characteristics using a bivariate ordinal regression model. This model is based on a latent bivariate normal random variable whose parameters are used to test the hypothesis that one of the map types is preferred over the other. Several additional characteristics are considered as potential covariates and found to make little practical difference in terms of the observed counts. It is seen that satellite maps are preferred to road maps in both familiarity and accuracy.

1 Introduction

Nichols et al. (2023+) present a study comparing the usability of two types of geographic maps: road maps provide a simplified display of an area while satellite maps give additional details such as landmarks and terrain. Figure 1 displays an example of each map type. A motivation for official statistics agencies—such as the U.S. Census Bureau—to understand map usability is their potential to crowdsource the identification of vacant housing units. For example, residents of an area may be able to identify and report local vacant units via mapping tools so that agencies can reduce costs of field operations to make this assessment. Knowledge of vacant housing units in turn facilitates agency field operations when contacting respondents to collect data. To this end, Nichols et al. (2023+) administered a survey on several characteristics of map usage. Respondents provided ordinal responses to several questions about both types of maps. Namely, respondents were to rate their familiarity with each type of map with possible responses: "not familiar at all", "slightly familiar", "moderately familiar", "very familiar", and "extremely familiar". Similarly, respondents were asked to report how accurately they could find their home and neighboring homes with each type of map, with possible responses: "not accurately at all", "slightly accurately", "moderately accurately", "very accurately", and "extremely accurately". A number of characteristics recorded along with familiarity and accuracy responses—such as age and level of education—are potential covariates. The survey was offered separately to two panels: a "census" panel with 160 respondents who self-selected to participate in Census Bureau research studies, and a "paid" panel of 315 respondents who were paid for their participation.

The present report seeks to answer two major questions from the survey data: (1) are individuals more familiar with one of the map types, and (2) do individuals feel that they can use one more accurately? Results

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(a) (b)

Figure 1: Examples of road map (a) and corresponding satellite map (b) displays used in the study.

may help to inform statistical agencies on the selection of a map display for crowdsourcing applications such as the identification of vacant housing units. Each of these questions are addressed using a bivariate ordinal model to compare pairs of preferences from each respondent. Here, ordinal observations are assumed to arise from latent bivariate normal random variables and their positions relative to cut point parameters. This is a special case of the multivariate ordinal regression model considered by Hirk et al. (2019). We will make use of the `mvord` package (Hirk et al., 2020) to facilitate fitting of such models in `R` (R Core Team, 2023). Ordinal regression is well-established in the literature (McCullagh, 1980), and may be considered as a multinomial regression model for categories which are ordered (Agresti, 2013, Chapter 8). A review of the literature on map usability, along with further details about the survey, are provided by Nichols et al. (2023+).

The remainder of the report proceeds as follows. Section 2 briefly reviews the bivariate ordinal regression model and the estimates and hypotheses of interest. Section 3 presents an analysis of the survey. Finally, Section 4 concludes the report.

2 Bivariate Ordinal Model

Consider n respondents, each with a pair of ordinal outcomes $\boldsymbol{y}_i = (y_{i1}, y_{i2})$ and a fixed covariate $\boldsymbol{x}_i \in \mathbb{R}^d$ for $i = 1, \ldots, n$. Each y_{ij} takes on values in $\{1, \ldots, K_j\}$, ordered from "least preferred" to "most preferred". Let $\boldsymbol{Y}_i = (Y_{i1}, Y_{i2})$ denote random variables which yield the observed $\boldsymbol{y}_i$. Adjusting for the covariate $\boldsymbol{x}_i$, we are interested in comparing which of the two outcome types represented by Y_{i1} and Y_{i2} is more preferred.

Suppose Y_{i1} and Y_{i2} are discretized versions of unobserved continuous random variables $\tilde{Y}_{i1}$ and $\tilde{Y}_{i2}$ such that

$$Y_{ij} = \begin{cases} 1, & \text{if } \gamma_{j0} < \tilde{Y}_{ij} \leq \gamma_{j1}, \\ 2, & \text{if } \gamma_{j1} < \tilde{Y}_{ij} \leq \gamma_{j2}, \\ \vdots & \vdots \\ K_j, & \text{if } \gamma_{jK_{j-1}} < \tilde{Y}_{ij} \leq \gamma_{jK_j}, \end{cases}$$

for $j = 1, 2$, with cut point parameters $\gamma_{j0} \leq \cdots \leq \gamma_{jK_j}$. The extreme cut points γ_{j0} and γ_{jK_j} are defined as $\gamma_{j0} \equiv -\infty$ and $\gamma_{jK_j} \equiv \infty$ and the others are free to vary subject to additional identifiability constraints to be discussed later in this section. It is assumed that

$$\tilde{Y}_{i1} = \boldsymbol{x}_i^\top \boldsymbol{\beta}_1 + \epsilon_{i1}, \quad \tilde{Y}_{i2} = \boldsymbol{x}_i^\top \boldsymbol{\beta}_2 + \epsilon_{i2}, \quad \boldsymbol{\epsilon}_i = (\epsilon_{i1}, \epsilon_{i2}) \stackrel{\text{iid}}{\sim} \text{BVN}(\mathbf{0}, \boldsymbol{\Sigma}), \quad \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix},$$

where $\text{BVN}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ represents the bivariate normal distribution with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. Therefore, ordinal observations $\boldsymbol{Y}_i$ from a common respondent may be positively or negatively correlated based on the sign of covariance parameter σ_{12}, and are assumed independent across respondents.

To write the likelihood based on observations $\{(\boldsymbol{y}_i, \boldsymbol{x}_i) : i = 1, \ldots, n\}$, first express the density of $[\boldsymbol{Y}_i \mid \tilde{\boldsymbol{Y}}_i]$ as

$$f(\boldsymbol{y}_i \mid \tilde{\boldsymbol{y}}_i) = \text{I}(\gamma_{1,y_{i1}-1} < \tilde{y}_{i1} \le \gamma_{1,y_{i1}}) \cdot \text{I}(\gamma_{2,y_{i2}-1} < \tilde{y}_{i2} \le \gamma_{2,y_{i2}}),$$

where $\text{I}(\cdot)$ is the indicator function. Recall that the joint distribution of $\tilde{\boldsymbol{Y}}_i \sim \text{BVN}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma})$ may be factored into

$$\tilde{Y}_{i1} \sim \text{N}(\mu_{i1}, \sigma_{11}), \quad \tilde{Y}_{i2} \mid \{\tilde{Y}_{i1} = \tilde{y}_{i1}\} \sim \text{N}(\vartheta_i(\tilde{y}_{i1}), \sigma^2_{2|1}),$$

where $\vartheta_i(w) = \mu_{i2} + \frac{\sigma_{12}}{\sigma_{11}}(w - \mu_{i1})$, $\sigma^2_{2|1} = \sigma_{22} - \sigma^2_{12}/\sigma_{11}$, and $\mu_{ij} = \boldsymbol{x}_i^\top \boldsymbol{\beta}_j$. Let $\phi(\cdot \mid \mu, \sigma^2)$ and $\Phi(\cdot \mid \mu, \sigma^2)$ represent the density and cumulative distribution function of the normal distribution with mean μ and variance σ^2. The likelihood can now be written via one-dimensional integrals

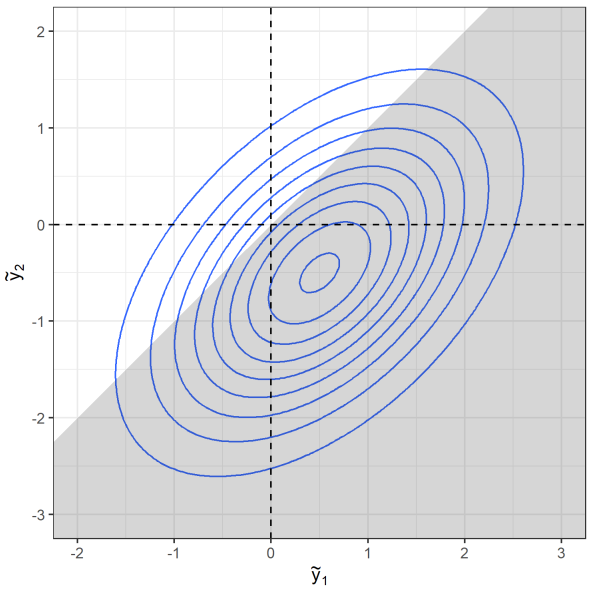
$$\begin{aligned} f_{\boldsymbol{\theta}}(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n) &= \prod_{i=1}^n \int \text{I}(\gamma_{1,y_{i1}-1} < \tilde{y}_{i1} \le \gamma_{1,y_{i1}})\, \text{I}(\gamma_{2,y_{i2}-1} < \tilde{y}_{i2} \le \gamma_{2,y_{i2}}) f_{\boldsymbol{\theta}}(\tilde{\boldsymbol{y}}_i) d\tilde{\boldsymbol{y}}_i \\ &= \prod_{i=1}^n \int_{\gamma_{1,y_{i1}-1}}^{\gamma_{1,y_{i1}}} \int_{\gamma_{2,y_{i2}-1}}^{\gamma_{2,y_{i2}}} f_{\boldsymbol{\theta}}(\tilde{\boldsymbol{y}}_i) d\tilde{y}_{i1} d\tilde{y}_{i2} \\ &= \prod_{i=1}^n \int_{\gamma_{1,y_{i1}-1}}^{\gamma_{1,y_{i1}}} \Big[\Phi(\gamma_{2,y_{i2}} \mid \vartheta_i(w), \sigma^2_{2|1}) - \Phi(\gamma_{2,y_{i2}-1} \mid \vartheta_i(w), \sigma^2_{2|1})\Big] \phi(w \mid \mu_{i1}, \sigma_{11}) dw. \end{aligned} \tag{1}$$

Hirk et al. (2019) note that some additional constraints on the parameters must be enforced for identifiability; namely, we will assume that $\sigma_{11} = \sigma_{22} = 1$, and $\gamma_{11} = \gamma_{21} = 0$ so that $\boldsymbol{x}_i$ may include an intercept. Now, σ_{12} is equivalent to the correlation $\rho = \sigma_{12}/\sqrt{\sigma_{11}\sigma_{22}}$, and the unknown parameters are $\boldsymbol{\theta} = (\gamma_{12}, \ldots, \gamma_{1,K_1-1}, \gamma_{22}, \ldots, \gamma_{2,K_2-1}, \boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \rho)$.

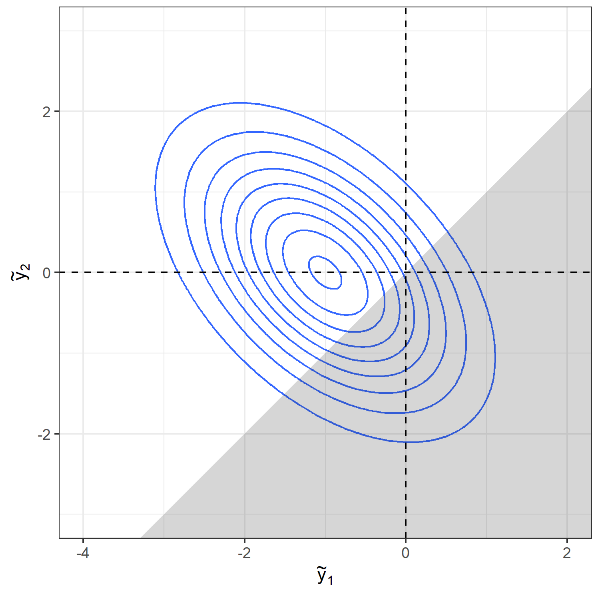
Under model (1), the first response type being more preferred than the second type is equivalent to $\text{P}(\tilde{Y}_{i1} > \tilde{Y}_{i2})$ being larger than $\text{P}(\tilde{Y}_{i1} \le \tilde{Y}_{i2})$, which furthermore is equivalent to

$$\begin{aligned} \frac{1}{2} &< \text{P}(\tilde{Y}_{i1} > \tilde{Y}_{i2}) \\ &= \text{P}\left(\frac{\tilde{Y}_{i1} - \tilde{Y}_{i2}}{\sqrt{\sigma_{11} + \sigma_{22} - 2\sigma_{21}}} > 0\right) \\ &= \text{P}\left(Z_i > -\frac{\boldsymbol{x}_i^\top(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2)}{\sqrt{\sigma_{11} + \sigma_{22} - 2\sigma_{21}}}\right) \\ &= \Phi\left(\frac{\boldsymbol{x}_i^\top(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2)}{\sqrt{2(1-\rho)}}\right) = \Phi(\boldsymbol{x}_i^\top \boldsymbol{\psi}), \end{aligned}$$

where $\boldsymbol{\psi} = (\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2)/\sqrt{2(1-\rho)}$ and $Z_i = \{(\tilde{Y}_{i1} - \tilde{Y}_{i2}) - \boldsymbol{x}_i^\top(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2)\}/\sqrt{\sigma_{11} + \sigma_{22} - 2\sigma_{21}}$ follows a $\text{N}(0, 1)$ distribution. Figure 2 displays two examples of BVN distributions illustrating the probability $\text{P}(\tilde{Y}_{i1} > \tilde{Y}_{i2})$. Now, $\Phi(\boldsymbol{x}_i^\top \boldsymbol{\psi}) > 1/2$ is equivalent to $\boldsymbol{x}_i^\top \boldsymbol{\psi} > 0$, so that the coefficients $\boldsymbol{\psi}$ may be interpreted in a similar way as traditional regression coefficients: a positive value of ψ_ℓ is associated with a higher preference for the first response type as the independent variable $x_{i\ell}$ increases, for $\ell = 1, \ldots, d$. Finally, note that $\text{P}(\tilde{Y}_{i1} > \tilde{Y}_{i2}) > 1/2$



(a) $\boldsymbol{\mu} = (0.5, -0.5)$, $\rho = 0.5$.



(b) $\boldsymbol{\mu} = (-1, 0)$, $\rho = -0.5$.

Figure 2: Two examples of $\tilde{\boldsymbol{Y}}_i \sim \text{BVN}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with $\sigma_{11} = \sigma_{22} = 1$. Contours represent the $\text{BVN}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ density $f_{\boldsymbol{\mu},\boldsymbol{\Sigma}}(\tilde{y}_{i1}, \tilde{y}_{i2})$ and the shaded region is where $\tilde{y}_{i1} > \tilde{y}_{i2}$. The probability $\text{P}(\tilde{Y}_{i1} > \tilde{Y}_{i2})$ is greater than 1/2 in (a) and less than 1/2 in (b).

can be determined based only on considering $\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2$; however, the degree to which $\text{P}(\tilde{Y}_{i1} > \tilde{Y}_{i2})$ exceeds 1/2 depends on ρ, so we prefer to consider $\boldsymbol{\psi}$. In $\boldsymbol{\psi}$, the values of $\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2$ are attenuated by a factor up to 2 when $\rho \approx -1$ and are increased when $\rho > 0$.

In light of this discussion, we consider two-sided hypotheses of the form

$$H_0 : \psi_\ell = 0 \quad \text{vs.} \quad H_1 : \psi_\ell \neq 0, \tag{2}$$

for $\ell \in \{1, \ldots, d\}$. Given estimates $\hat{\boldsymbol{\theta}}$ of $\boldsymbol{\theta}$, a point estimate of $\boldsymbol{\psi}$ is given by $\hat{\boldsymbol{\psi}} = (\hat{\boldsymbol{\beta}}_1 - \hat{\boldsymbol{\beta}}_2)/\sqrt{2(1-\hat{\rho})}$. Standard errors of $\boldsymbol{\psi}$ are computed using an estimator of the large sample variance $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\psi}}) = \boldsymbol{J}_{\boldsymbol{\psi}(\hat{\boldsymbol{\theta}})} \hat{\boldsymbol{V}}(\hat{\boldsymbol{\theta}}) \boldsymbol{J}_{\boldsymbol{\psi}(\hat{\boldsymbol{\theta}})}^\top$, where $\boldsymbol{J}_{\boldsymbol{\psi}(\boldsymbol{\theta})}$ is the Jacobian of the transformation from $\boldsymbol{\theta}$ to $\boldsymbol{\psi}$ and $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\theta}})$ is an estimate of the variance of $\hat{\boldsymbol{\theta}}$ obtained from the `mvord` package.[1] To test (2), a p-value is obtained by forming a z-value from the corresponding element of $\hat{\boldsymbol{\psi}}$ and the associated standard error; in particular, the p-value is computed as $2 \cdot \Phi(-|\hat{\psi}_\ell / \sqrt{\hat{v}_{\ell\ell}}|)$, where $\hat{v}_{ab}$ is the element in the ath row and bth column of $\hat{\boldsymbol{V}}(\hat{\boldsymbol{\psi}})$. An observed value of $\hat{\psi}_\ell / \sqrt{\hat{v}_{\ell\ell}}$ with a large magnitude results in a smaller p-value and serves as evidence against H_0.

3 Data Analysis

We will consider four variations of model (1). In all cases, Y_{i1} and Y_{i2} will be taken to represent ordinal responses on road maps and satellite maps, respectively. Analyses comparing map familiarity and map accuracy will be carried out separately. Furthermore, census and paid panels are analyzed separately due to differences in how they were selected for the survey and potential differences in the two populations which may not be explicitly captured in the data.

[1]`mvord` maximizes a pairwise composite likelihood for the general multivariate ordinal model, but this appears to be equivalent to maximum likelihood in the bivariate case.

Table 1: Likelihood ratio tests of null model versus full model, in each of the four model variations. The column labeled "DF" represents degrees of freedom of the test.

Outcome	Panel	Statistic	DF	p-value
Familiarity	Census	76.051	38	2.4145E-04
Familiarity	Paid	90.954	44	4.0801E-05
Accuracy	Census	51.069	38	0.0764
Accuracy	Paid	82.639	44	3.7658E-04

Initially, familiarity and accuracy responses are coded with five common levels: 1 = `not at all`, 2 = `slightly`, 3 = `moderately`, 4 = `very`, and 5 = `extremely`. Other survey responses are used as covariates: `area_type` with levels `rural`, `suburban`, `urban`, and `unsure`; `home_type` with levels `detached`, `attached`, `apartment`, `mobile`, and `other`; home ownership `own` with levels `true` and `false`; length of tenure at a residence `tenure` with levels `<1 year`, `1-2 years`, `2-5 years`, `5-10 years`, `10-20 years`, and `>20 years`; education level `educ` with levels `less than high school`, `completed high school`, `some college but no degree`, `associate's degree`, `bachelor's degree`, and `post-bachelor's degree`; and `age` with levels `18-24`, `25-34`, `35-50`, `51-65`, and `>65`.

For the census panel, levels of some variables were combined to avoid small counts. Familiarity and accuracy were coarsened and recoded to three levels: 1 = {`not at all`, `slightly`, `moderately`} , 2 = { `very` }, and 3 = { `extremely` }. Education level `educ` was recoded to four levels so that `less than high school`, `completed high school`, `some college but no degree` are combined. Variable `age` was recoded to four levels, combining `18-24` and `25-34`. One respondent with a missing value for `tenure` was dropped from the analysis. No such collapsing of categories was applied to the paid panel.

For each of the four model variations, we considered a "full" model where $\boldsymbol{x}_i$ encodes all available covariates, and a "null" model where $\boldsymbol{x}_i$ contains only an intercept. Table 1 shows that in each case, the null model can be rejected in favor of the full model at a 0.10 significance level. However, further diagnostic analysis shows that there is little practical change between the two models in each case. Namely, Tables 2, 3, 4, 5 present observed counts $n_{ab} = \sum_{i=1}^{n} \mathrm{I}(y_{i1} = a, y_{i2} = b)$ along with expected counts

$$N_{ab}(\boldsymbol{\theta}) = \sum_{i=1}^{n} \mathrm{P}_{\boldsymbol{\theta}}(Y_{i1} = a, Y_{i2} = b), \quad \text{for } a \in \{1, \ldots, K_1\} \text{ and } b \in \{1, \ldots, K_2\}, \tag{3}$$

evaluated at the estimates $\hat{\boldsymbol{\theta}}$ obtained under the full model and the null model, for each of the two outcome types. Expected counts from the two full models are practically not much closer to the observed counts than the null models; therefore, we proceed with the null model in each case.

Tables 6 and 7 display estimates for the null models fit to the census and paid panels, respectively. Estimates for ρ indicate positive correlation between the two map types for both familiarity and accuracy. Furthermore, estimates of $\psi = (\beta_{01} - \beta_{02})/\sqrt{2(1-\rho)}$ are negative, which indicates that satellite maps are higher than road maps in both self-reported familiarity and accuracy. Results largely agree between census and paid panels; one notable difference being a more extreme estimate of $\hat{\psi} = -0.9499$ (with associated p-value 1.009E-05) for accuracy in the census panel, compared to $\hat{\psi} = -0.4875$ (with p-value 7.279E-03) for the paid panel. Therefore, while more accurate use of satellite maps is reported in both panels, the evidence is stronger in the census panel.

4 Conclusions

A bivariate ordinal model was used to analyze pairs of ordinal responses from respondents in two related surveys. The responses represented ratings of two alternative options—in this case satellite maps and road maps—and our interest was to determine if one was preferred to the other. Coefficients were identified to capture this preference in relation to available covariates and to test statistical hypotheses for it. In this

Table 2: Observed and expected counts (3) of familiarity for road and satellite maps among paid panel. Categories are coded as: 1 = `not at all`, 2 = `slightly`, 3 = `moderately`, 4 = `very`, and 5 = `extremely`.

(a) Full Model.

	Road				
Sat	1	2	3	4	5
1	8.35	7.06	9.25	5.54	1.18
2	2.91	4.94	10.33	10.14	3.68
3	2.09	5.04	14.57	20.95	12.26
4	0.93	3.32	14.17	32.33	35.05
5	0.14	0.79	5.62	24.17	80.19

(b) Null Model.

Road				
1	2	3	4	5
7.96	6.72	9.26	5.76	1.22
2.98	4.78	10.21	10.23	3.65
2.24	5.02	14.65	21.46	12.31
1.01	3.28	14.00	32.73	35.17
0.15	0.75	5.32	23.66	80.47

(c) Observed.

Road				
1	2	3	4	5
13	4	4	6	3
0	8	9	9	5
0	6	18	16	17
1	1	15	46	25
1	0	6	20	82

Table 3: Observed and expected counts (3) of accuracy for road and satellite maps among paid panel. Categories are coded as: 1 = `not at all`, 2 = `slightly`, 3 = `moderately`, 4 = `very`, and 5 = `extremely`.

(a) Full Model.

	Road				
Sat	1	2	3	4	5
1	6.64	6.55	10.48	6.13	1.16
2	3.14	5.55	14.17	13.93	4.60
3	2.15	5.31	19.26	29.14	16.30
4	0.75	2.62	14.12	34.72	36.29
5	0.10	0.51	4.43	20.02	56.93

(b) Null Model.

Road				
1	2	3	4	5
6.74	6.15	10.04	6.26	1.21
3.38	5.53	14.02	14.43	4.84
2.28	5.26	18.87	29.75	16.84
0.77	2.55	13.57	34.67	36.57
0.10	0.49	4.20	19.77	56.71

(c) Observed.

Road				
1	2	3	4	5
11	6	5	4	4
1	6	16	14	4
1	4	23	21	25
0	2	13	50	25
1	1	2	18	58

Table 4: Observed and expected counts (3) of familiarity for road and satellite maps among census panel. Categories are coded as: 1 = {`not at all`, `slightly`, `moderately`}, 2 = {`very`}, and 3 = {`extremely`}.

(a) Full Model.

	Road		
Sat	1	2	3
1	13.37	16.52	6.78
2	4.412	17.34	19.94
3	1.287	12.72	66.63

(b) Null Model.

Road		
1	2	3
13.35	15.67	7.06
4.48	16.72	20.13
1.43	13.10	67.06

(c) Observed.

Road		
1	2	3
14	12	10
3	23	16
2	11	68

Table 5: Observed and expected counts (3) of accuracy for road and satellite maps among census panel. Categories are coded as: 1 = {`not at all`, `slightly`, `moderately`}, 2 = {`very`}, and 3 = {`extremely`}.

(a) Full Model.

	Road		
Sat	1	2	3
1	18.07	23.99	13.53
2	3.01	16.11	26.72
3	0.43	6.08	51.06

(b) Null Model.

Road		
1	2	3
18.06	24.07	12.71
2.87	15.87	27.56
0.44	6.31	51.11

(c) Observed.

Road		
1	2	3
14	20	22
5	17	24
0	9	48

Table 6: Null models for census panel.

(a) Familiarity.

	Estimate	SE	p-value
γ_{12}	0.7160	0.1034	4.410E-12
γ_{22}	0.9348	0.1271	1.896E-13
β_1	0.7489	0.1129	3.324E-11
β_2	1.1694	0.1315	< 2.2E-16
ψ	-0.5345	0.1858	4.009E-03
ρ	0.6905	0.0625	< 2.2E-16

(b) Accuracy.

	Estimate	SE	p-value
γ_{12}	0.7472	0.1012	1.502E-13
γ_{22}	0.9174	0.1261	3.441E-13
β_1	0.3993	0.1031	1.071E-04
β_2	1.1058	0.1303	< 2.2E-16
ψ	-0.9499	0.2151	1.009E-05
ρ	0.7234	0.0606	< 2.2E-16

Table 7: Null models for paid panel.

(a) Familiarity.

	Estimate	SE	p-value
γ_{12}	0.4478	0.0776	7.795E-09
γ_{13}	0.9761	0.0967	< 2.2E-16
γ_{14}	1.6764	0.1132	< 2.2E-16
γ_{22}	0.4676	0.1063	1.091E-05
γ_{23}	1.1084	0.1263	< 2.2E-16
γ_{24}	1.8876	0.1368	< 2.2E-16
β_1	1.2920	0.1031	< 2.2E-16
β_2	1.6899	0.1285	< 2.2E-16
ψ	-0.4889	0.1990	1.401E-02
ρ	0.6688	0.0356	< 2.2E-16

(b) Accuracy.

	Estimate	SE	p-value
γ_{12}	0.5642	0.0829	9.848E-12
γ_{13}	1.2067	0.0990	< 2.2E-16
γ_{14}	1.9511	0.1167	< 2.2E-16
γ_{22}	0.4761	0.1050	5.754E-06
γ_{23}	1.1971	0.1283	< 2.2E-16
γ_{24}	2.0616	0.1399	< 2.2E-16
β_1	1.3015	0.1010	< 2.2E-16
β_2	1.7266	0.1291	< 2.2E-16
ψ	-0.4875	0.1817	7.279E-03
ρ	0.6200	0.0373	< 2.2E-16

setting, we found that covariates made little practical difference, and that satellite maps are higher than road maps in both self-reported familiarity and accuracy for both surveys. We analyzed familiarity and accuracy separately, but one might also consider a joint model at the cost of increased computational complexity.

Acknowledgments

This report is released to inform interested parties of ongoing research and to encourage discussion of work in progress. It has been reviewed for disclosure avoidance and approved under CBDRB–FY23–213. Any views expressed are those of the authors and not those of the U.S. Census Bureau. We thank Jessica Holzberg (Center for Behavioral Science Methods), Darcy Steeg Morris (Center for Statistical Research and Methodology), and Tommy Wright (Center for Statistical Research and Methodology) for their feedback on the manuscript and Shaun Genter (Center for Behavioral Science Methods) for guidance with the disclosure review process.

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