Multivariate Tests for Phase Capacity

Federal CASIC Workshops (FedCASIC)
U.S. Census Bureau Headquarters
Suitland, MD
March 4, 2015

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¹The opinions, findings, and conclusions expressed in this presentation are those of the author and do not necessarily reflect those of the U.S. Office of Personnel Management.
Outline

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I. Background
Nonresponse and Nonrespondent Follow-Up

- Invariably, not all sampled units respond to the initial survey solicitation

- Most surveys repeatedly follow-up with nonrespondents making additional mailings, phone calls, household visits, etc., often chasing a preset response rate target

- Each subsequent reminder brings in a new “wave” of data, which tends to be progressively smaller in size, thereby impacting estimates less and less

- Other temporal delineations of waves possible
The Notion of Phase Capacity

• In their discussion of responsive survey design, Groves and Heeringa (2006) define the following key terms:
  – design phase – spell of data collection period with stable frame, sample, and recruitment protocol
  – phase capacity – point during a design phase at which additional responses cease influencing key statistics

• Rather than fixating on a target response rate, they argue one should change design phases (e.g., switch mode, increase incentive) or discontinue nonrespondent follow-up altogether once phase capacity has been reached

• Problem for practitioners: no calculable rule given
Illustration of Phase Capacity in the Federal Employee Viewpoint Survey (FEVS)

• The FEVS is an annual organizational climate survey administered by the U.S. Office of Personnel Management (OPM) to a sample of 800,000+ federal employees from 80+ agencies

• Web-based instrument comprised mainly of attitudinal items posed on a five-point Likert scale

• Key statistics are “percent positive” estimates based on the dichotomization of, for example, “Completely Agree” or “Agree” elections versus all other possible response choices

• Nonrespondents are sent weekly reminder emails
Example of a Nonresponse-Adjusted Percent Positive Trend Using Cumulative Responses

Goal is to identify point estimate stability at earliest possible wave

Note: estimate stability does not necessarily imply that the value converged upon is free of nonresponse error; it implies that additional follow-ups under the same protocol will continue to be ineffectual.
II. Brief Summary of Prior Research – Univariate Phase Capacity Tests
Previously Proposed Univariate Tests


• Idea is to multiply impute (Rubin, 1987) the missing data $M (M \geq 2)$ times for nonrespondents as of wave $k$, then delete responses obtained during wave $k$, specifically, and repeat for nonrespondents as wave $k – 1$ → result is $2M$ completed data sets and two nonresponse-adjusted, MI point estimates

• A $t$-test is carried out by dividing the two point estimates’ difference by an estimate of the MI variance of the difference – see Appendix A of Lewis (2014a) for example

• Phase capacity declared once the test statistic is insignificant
Previously Proposed Univariate Tests (2)

- RGG approach is limited in that it is only designed to track a sample mean and inapplicable to surveys that conduct weighting adjustments for nonresponse

- Lewis (2014b) describes a new method circumventing these limitations: same premise, except nonresponse-adjusted point estimates are formulated based on two sets of weights, one for respondents through wave \( k \) and another for respondents through wave \( k - 1 \)

- As with the RGG approach, tricky part is deriving a variance factoring in the covariance attributable to shared respondent set through wave \( k - 1 \)

- Three viable methods to do so are discussed: (1) Taylor series linearization; (2) simple linear regression on a stacked data set; and (3) replication
III. Multivariate Extensions of Phase Capacity Tests
Background

• A practical limitation of both the RGG approach and Lewis’ variant is that they are univariate in nature → how would one proceed if independently conducted on two or more point estimates with conflicting results?

• Chapter 4 of Lewis (2014a) proposes two multivariate methods to provide a single yes/no answer for a battery of $D$ point estimates:
  1. Wald Chi-Square Method – direct multivariate extension of two-sample $t$-test using matrix algebra
  2. Non-Zero Trajectory Method – based on ideas of longitudinal data analysis (Singer and Willett, 2003), jointly fit $D$ simple linear regression models of point estimates’ relative percent change

• Both methods default to treating each point estimate difference equivalently, but differential importance can be assigned to each via a contrast vector
Wald Chi-Square Method

- Let $\mathbf{D}$ denote a $D \times 1$ matrix of nonresponse-adjusted point estimate differences, and let $\mathbf{S}$ denote the corresponding $D \times D$ variance-covariance matrix.

- Entries of $\mathbf{S}$ can be obtained via Taylor series linearization or replication (i.e., as discussed in Lewis (2014b)).

- Supposing the goal is to test for no significant differences, the test statistic is

$$
\chi^2_W = \mathbf{D}^T \mathbf{S}^{-1} \mathbf{D}
$$

which is referenced against a chi-square distribution with $D - 1$ degrees of freedom.
Non-Zero Trajectory Method

- Find the $D$ differences’ 3 most recent relative percent changes (to harmonize potential scale incongruities):

<table>
<thead>
<tr>
<th>Wave</th>
<th>Item 4</th>
<th>Rel % Chg</th>
<th>Item 5</th>
<th>Rel % Chg</th>
<th>Item 13</th>
<th>Rel % Chg</th>
</tr>
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<tbody>
<tr>
<td>$k - 3$</td>
<td>75.2%</td>
<td>--</td>
<td>83.6%</td>
<td>--</td>
<td>88.5%</td>
<td>--</td>
</tr>
<tr>
<td>$k - 2$</td>
<td>75.3%</td>
<td>0.2%</td>
<td>83.8%</td>
<td>0.2%</td>
<td>88.6%</td>
<td>0.1%</td>
</tr>
<tr>
<td>$k - 1$</td>
<td>75.7%</td>
<td>0.5%</td>
<td>83.9%</td>
<td>0.2%</td>
<td>88.6%</td>
<td>0.0%</td>
</tr>
<tr>
<td>$k$</td>
<td>76.1%</td>
<td>0.4%</td>
<td>84.2%</td>
<td>0.3%</td>
<td>88.7%</td>
<td>0.2%</td>
</tr>
</tbody>
</table>

- Treating $w$ as a wave indicator one unit apart (e.g., 1, 2, 3), one then estimates the following model:

$$
\Delta_d = \beta_0 + \beta_2 + \ldots + \beta_{D} + \beta_{11}w + \beta_{12}w + \ldots + \beta_{1D}w + \epsilon_d
$$

where the first set of $D$ terms represent estimate-specific intercepts, and the second set represents estimate-specific slopes.

- Disadvantage: at least 4 waves needed (Wald needs 2)
If point estimates have stabilized, we would expect all model coefficients to be insignificantly different from zero; we can test for this using a traditional linear model $F$ test

$$F = \hat{\beta}^T (\text{cov}(\hat{\beta}))^{-1} \hat{\beta}$$

which can be referenced against an $F$ distribution with $D$ and $2D$ degrees of freedom, respectively.
IV. Retrospective Application using the 2011 Federal Employee Viewpoint Survey
FEVS 2011 Application Details

• Batteries of point estimates investigated were the four Human Capital Assessment and Accountability Framework (HCAAF) indices, which are averages of the percent positive estimates of thematically-linked items (e.g., Job Satisfaction, Talent Management)

• Using timestamp information for three agencies, respondents were apportioned into waves, and each successive (accumulating) set of respondents was assigned a set of weights raked to known marginal distributions from sample frame (e.g., agency component, minority status, gender, and supervisory status)

• Retroactively implemented the two methods for each agency x index combination to compare and contrast performance
Wald method concludes phase capacity earlier, in part because it requires fewer waves (2 vs. 4 for NZT); this results in larger residual differences relative to the final wave estimate (see NR Error column) – recall there is an upward trend in the point estimates underlying indices.

<table>
<thead>
<tr>
<th>Index</th>
<th>Stopping Wave</th>
<th>Estimate</th>
<th>NR Error</th>
<th>Stopping Wave</th>
<th>Estimate</th>
<th>NR Error</th>
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<tr>
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<td>-0.6</td>
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<td>-0.2</td>
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<td>9</td>
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<td></td>
<td></td>
<td></td>
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<td>-1.0</td>
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<td>0.1</td>
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<td>5</td>
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<td></td>
<td></td>
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<tr>
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<td>6</td>
<td>73.5</td>
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</tr>
<tr>
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<td>-1.3</td>
<td>7</td>
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<td>-0.6</td>
<td>5</td>
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<td>-0.5</td>
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<tr>
<td>TM</td>
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<td>69.4</td>
<td>-1.0</td>
<td>6</td>
<td>70.2</td>
<td>-0.2</td>
</tr>
</tbody>
</table>
V. Limitations and Further Research
Practical Limitations

• Actual adoption of these approaches in FEVS would face resistance because:
  – Desirable to treat each agency equitably; beginning in FEVS 2012, field period was preset to 6 weeks for all agencies
  – Higher scores are better, and so there may be opposition to any change, shortened field period included, believed to reduce point estimates

• Data must be collected/processed real-time, and it was tacitly assumed that the full sample is “active” – may be impractical for in-person surveys covering a vast geographical expanse taking weeks or months for interviewers to exhaust sample cases, although tests could be applied to subsamples
Practical Limitations (2)

• Even when entire sample is “active,” may not be feasible to send reminders simultaneously as in the FEVS Web mode – alternative data collection wave definition may be a plausible work-around

• Despite aversion to phrase stopping rule, stopping was the only design phase change investigated in this research – would be interesting to apply in a sequential mixed-mode survey setting or in surveys with two stages of data collection, such as the National Immunization Survey (NIS) or the Residential Energy Consumption Survey (RECS)

• In both of those surveys, the preeminent estimates are those derived from secondary data collection stage, medical records (NIS) and energy suppliers (RECS); hence, one might want the tests to have differential sensitivities
Further Research

• A general limitation of the two traditional perspectives of nonresponse (deterministic vs. stochastic) is that the act of responding is considered a dichotomous event.

• Chapter 2 of Lewis (2014a) extends the familiar sample mean nonresponse error/bias theory to account for a time dimension:
  • *Deterministic perspective* – conceptualize sample frame as composed of $K + 1$ mutually exclusive domains, units that always respond during wave $k$ ($k = 1, \ldots, K$), specifically, and a domain for units that never respond.
  • *Stochastic perspective* – partition a unit’s traditional response propensity into a vector of $K$ wave-specific propensities, the sum of which constitutes its overall propensity.

• To be presented at the TSE15 conference later this year.
Further Research (2)

• Wagner and Raghunathan (2010) proposed a prospective stopping rule, aiming to quantify the likelihood a pending wave of follow-up will change a point estimate more than some predetermined amount.

• Chapter 5 of Lewis (2014a) points out several limitations and introduces a more general approach; unfortunately, results were lackluster in simulation and application, even when the expected value of the point estimate was stable over the data collection period.

• Applications of time series analysis and forecasting could prove fruitful, especially if predictions beyond wave $k + 1$ are desired.
Thanks!

Questions/Comments?
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References


