Estimating response propensity and nonresponse bias for the 2022 Agricultural Production Census

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The Agricultural Production Census

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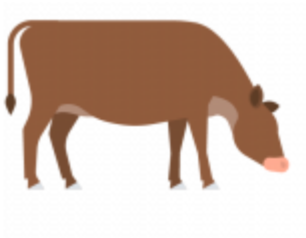
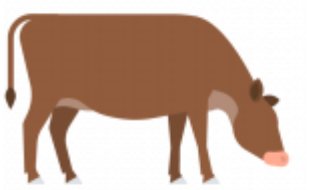
- Undertaken every 5 years in partnership with the Ministry of Primary Industries
- Aims to provide a range of summary statistics on the agricultural industry in New Zealand (e.g., total number of cows).
- Target population is all businesses engaged in agricultural production activity during the year ended
- Despite being a survey, we have information on both responding an non responding farms.
- High-level strata consist of a combination of region and farm types
- The final stratification variable is the total land area of each farm measured in hectares.



The Agricultural Production Census

- In 2022 the APC had an atypical low response rate of 69%
- In comparison, in the 2017 census the response rate was 84%
- In addition to the general tendency of low response rates, Groundswell NZ called for all farmers and growers to boycott the APC
- Historically, nonresponse has been handled by donor imputation
- Low response rates can potentially introduce nonresponse bias.



Nonresponse bias

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- Decreasing response rates may not always lead to nonresponse bias. Low response rates are not necessarily “bad” per se.
- Nonresponse bias occurs as a function of how correlated response propensity is to the attributes measured.
- Within the same survey, nonresponse bias can vary across different variables.
- To discern when nonresponse rates lead to nonresponse bias, we must understand how the influences for and against participation are related to the survey measures.

Can nonresponse bias actually be quantified?

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- Nonresponse bias is notoriously difficult to estimate because we do not know the nonrespondent's values.
- The bias estimation based on the sample respondents will not equal the population bias (i.e., you need the whole population)
- Bias approximations also need Y values for the nonrespondents (which we do not know), or some approximation of them (based on variables that correlate with them).
- Imputation assigns Y values to nonrespondents.
- All the expressions that relate response propensities to nonresponse bias are based on approximations because the estimators are nonlinear.
- While approximations are quite good in many cases, they may be less precise in some situations.

Response propensity

$$\phi_i = \phi(x_i) = \Pr(R_i = 1 | X = x_i)$$

- ϕ_i The response propensity for unit i
- x_i Auxilary data for unit i
- $R_i = 1$ If unit i responds

- Response propensities are unknown, we observe only the binary outcome of response or nonresponse
- We often have auxiliary data available for all sampled units that can be used to understand/adjust for non response
- We assume that $\phi_i > 0$ for all *i*
- Response propensities are often estimated by logistic regression, but probit and non parametric methods can also be used.
- Response propensities are dynamic and likely to vary with the recruitment protocol

Brick, J. M. (2013). Unit nonresponse and weighting adjustments: A critical review. *Journal of Official Statistics*, *29*(3), 329-353.

Response propensity

- What causes a survey variable to be correlated to the likelihood to respond?

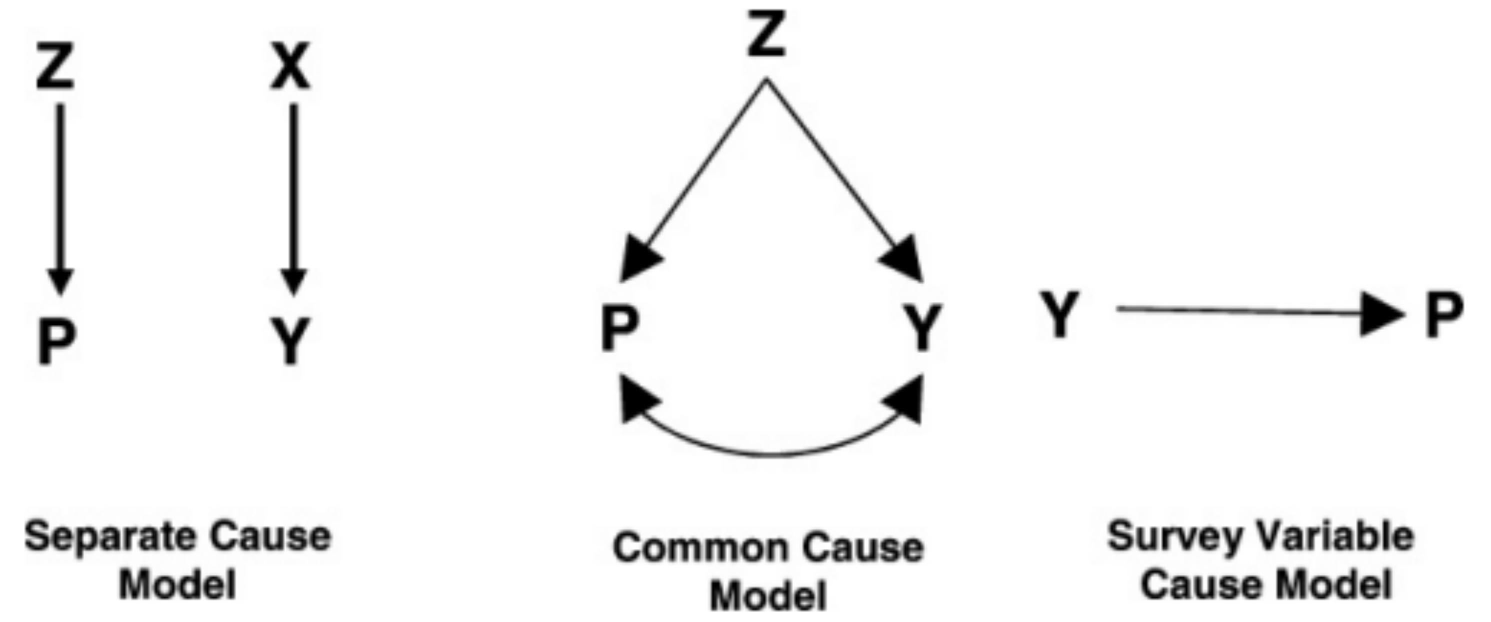


Figure 1. Three Relevant Causal Models Linking Response Propensity with Nonresponse Bias.

Groves, R. M., & Peytcheva, E. (2008). The impact of nonresponse rates on nonresponse bias: a meta-analysis. *Public opinion quarterly*, *72*(2), 167-189.

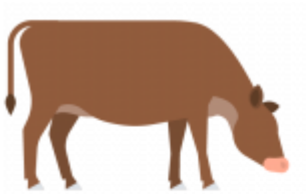
Response propensity weight adjustment

$$\hat{y} = \sum_i d_i \phi_i^{-1} y_i$$

- An method to adjust for nonresponse
- The adjustment factor is the inverse of the estimated propensities of the respondents.
- The idea is to replace the unknown probability of response by an estimate

Research questions

- Which auxiliary variables best correlate with response propensities for the APC?
- Did response propensities change between 2017 to 2022?
- Is there evidence of nonresponse bias in key variables in the Agricultural Production Census?
- Does response propensity weight adjustment give different results to donor imputation?
- Can nonresponse bias decrease with response propensity weight adjustment?



Response propensity model

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$$\text{response}_i \sim \text{Binomial}(1, p_{i,j})$$

$$p_{i,j} = \alpha_{\text{cell}[j]} + \beta_{\text{s,cell}[j]}\text{size}_i + \beta_{\text{r,cell}[j]}\text{past responses}_i$$

$$\begin{bmatrix} \alpha_{\text{cell}} \\ \beta_{\text{s,cell}} \\ \beta_{\text{r,cell}} \end{bmatrix} \sim \text{MVNormal}\left(\begin{bmatrix} \alpha \\ \beta_s \\ \beta_r \end{bmatrix}, \mathbf{\Sigma} \right)$$

$$\mathbf{\Sigma} = \mathbf{SRS}$$

$$\alpha \sim \text{Normal}(0, 1.5)$$

$$\beta_s \sim \text{Normal}(0, 0.5)$$

$$\beta_r \sim \text{Normal}(0, 0.5)$$

$$\sigma_\alpha \sim \text{Exponential}(1)$$

$$\sigma_{\beta_s} \sim \text{Exponential}(1)$$

$$\sigma_{\beta_r} \sim \text{Exponential}(1)$$

$$\mathbf{R} \sim \text{LKJcorr}(2),$$

- Multilevel Bayesian logistic model
- Imputation cell as a random effect (i.e., each cell had its own intercept and slope)
- Imputation cells are a combination of farm type, region and a range of sizes.
- Predictor variables : size (log transformed) and number of past responses.

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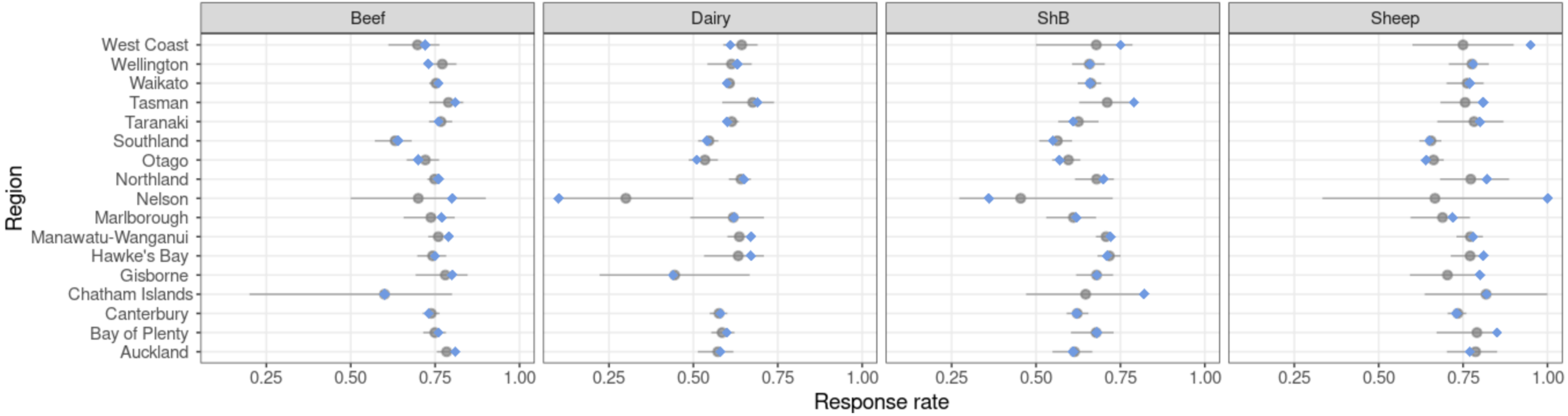
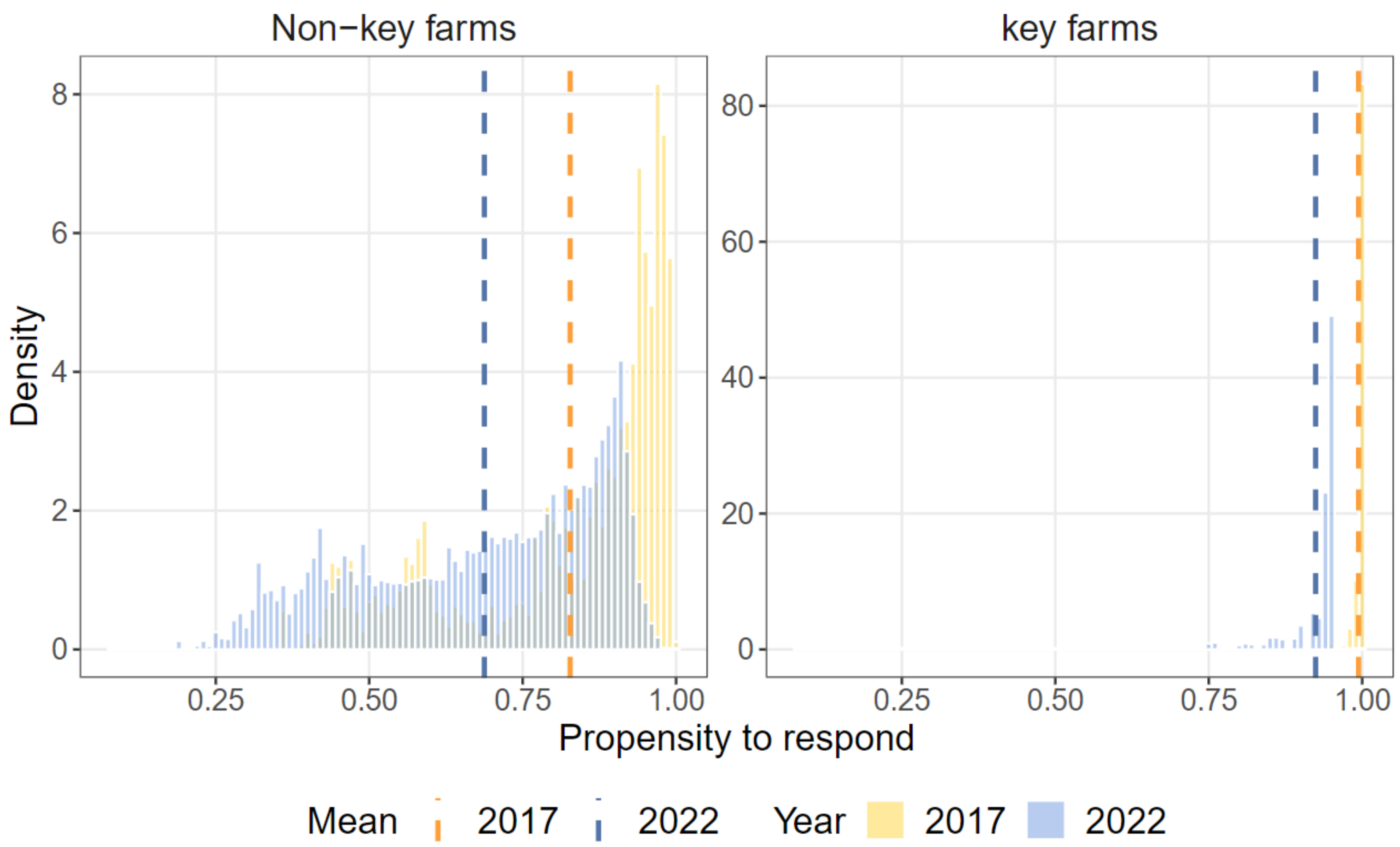
- Adjusted this model to 2017 and 2022 census data.
- Model comparison with LOOIC showed this is the best fit model for both sets of data compared to less complex models (e.g., only intercept)

Response propensity model



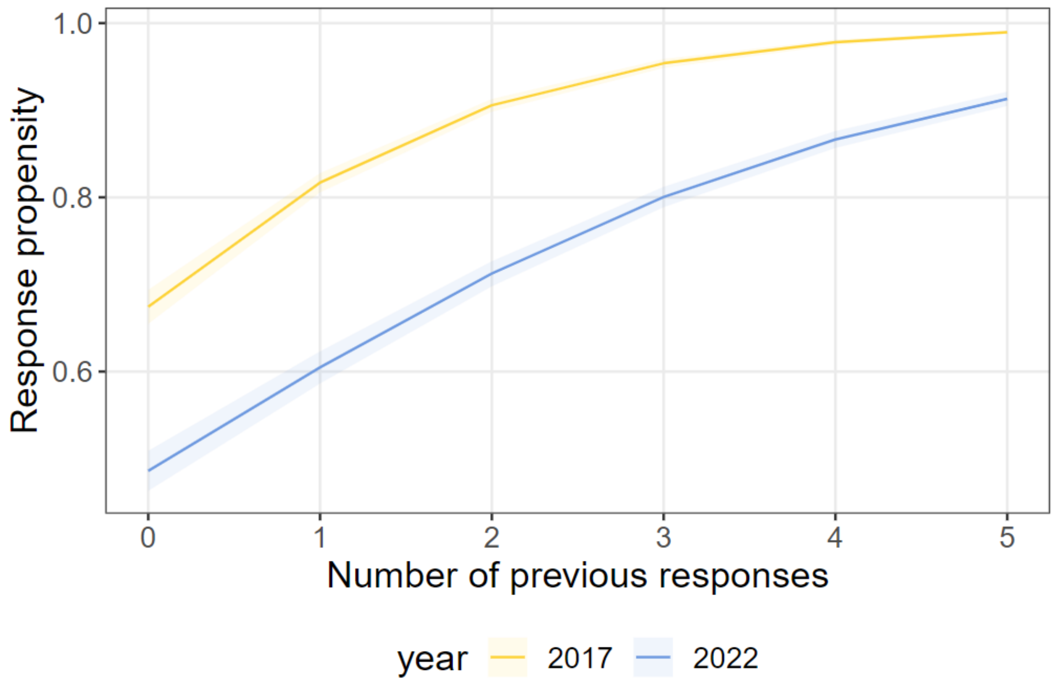
- Posterior predictive checks showed this model is a relatively good fit to the data (figure shows 2022).
- Blue points are observed response rates while grey points and lines are median and 90% of the highest posterior density

Response propensity model



Posterior draws of the expected value of the posterior predictive distribution for every observation in 2017 and in 2022

Response propensity model



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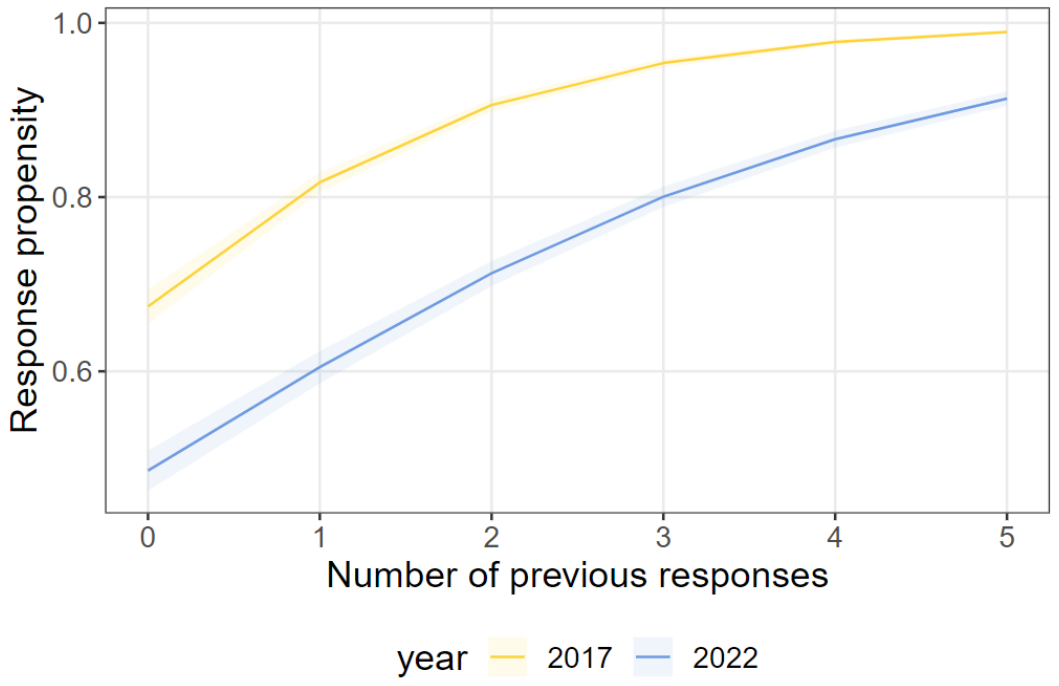
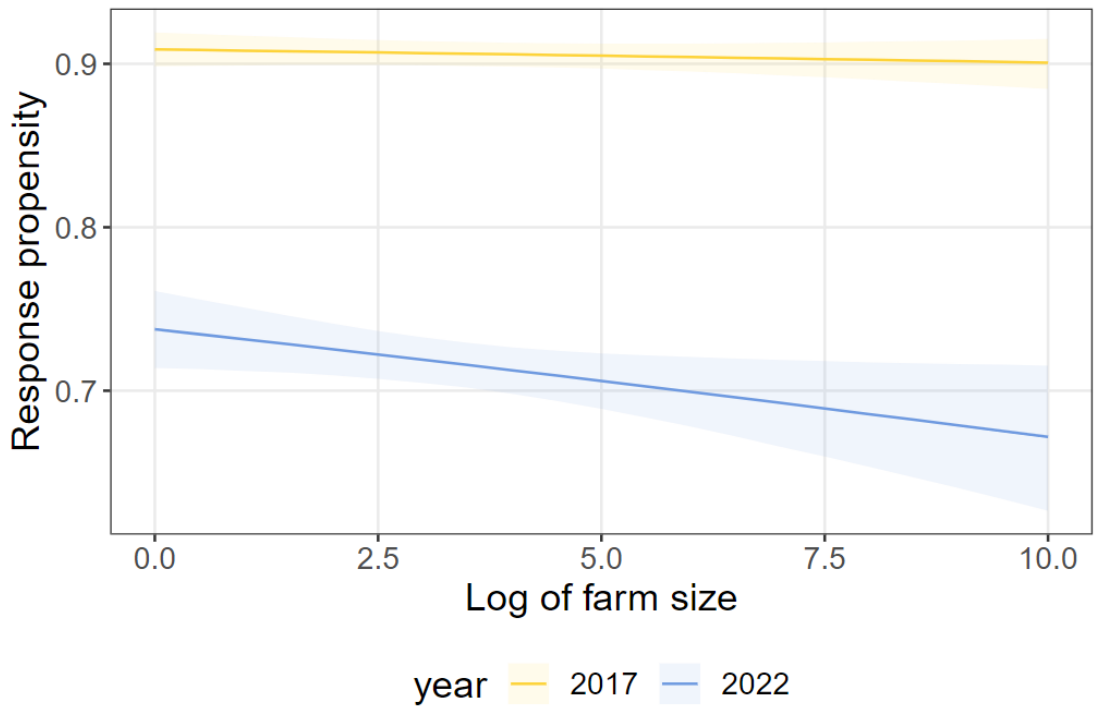
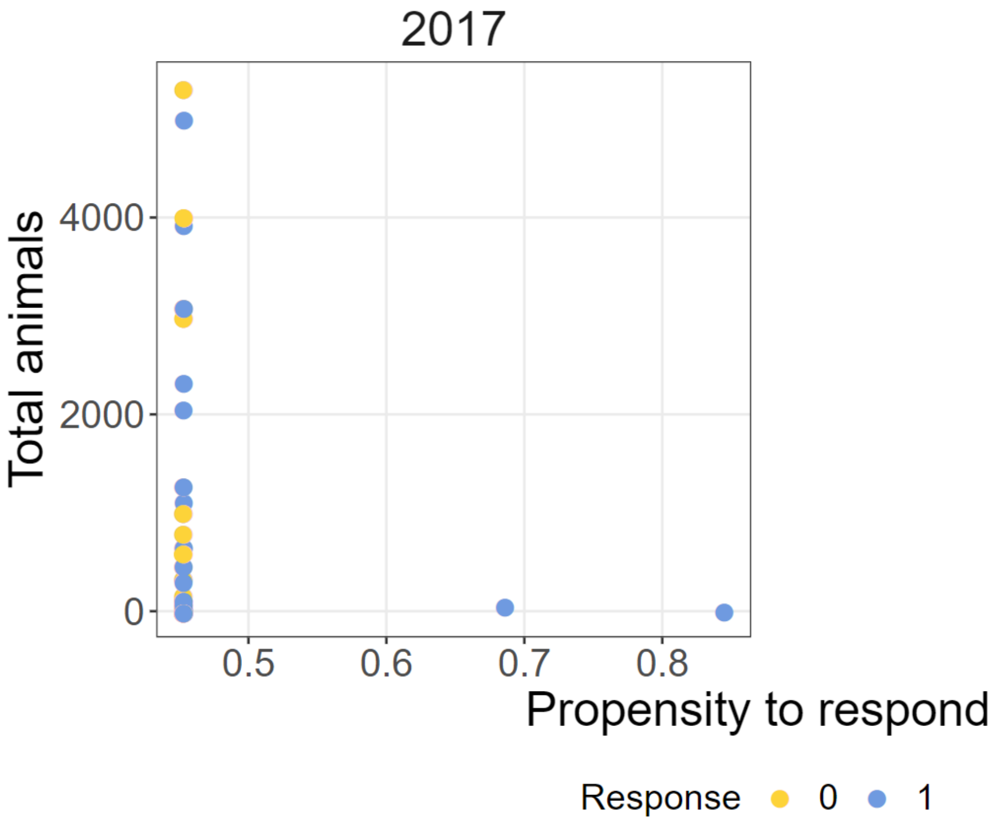


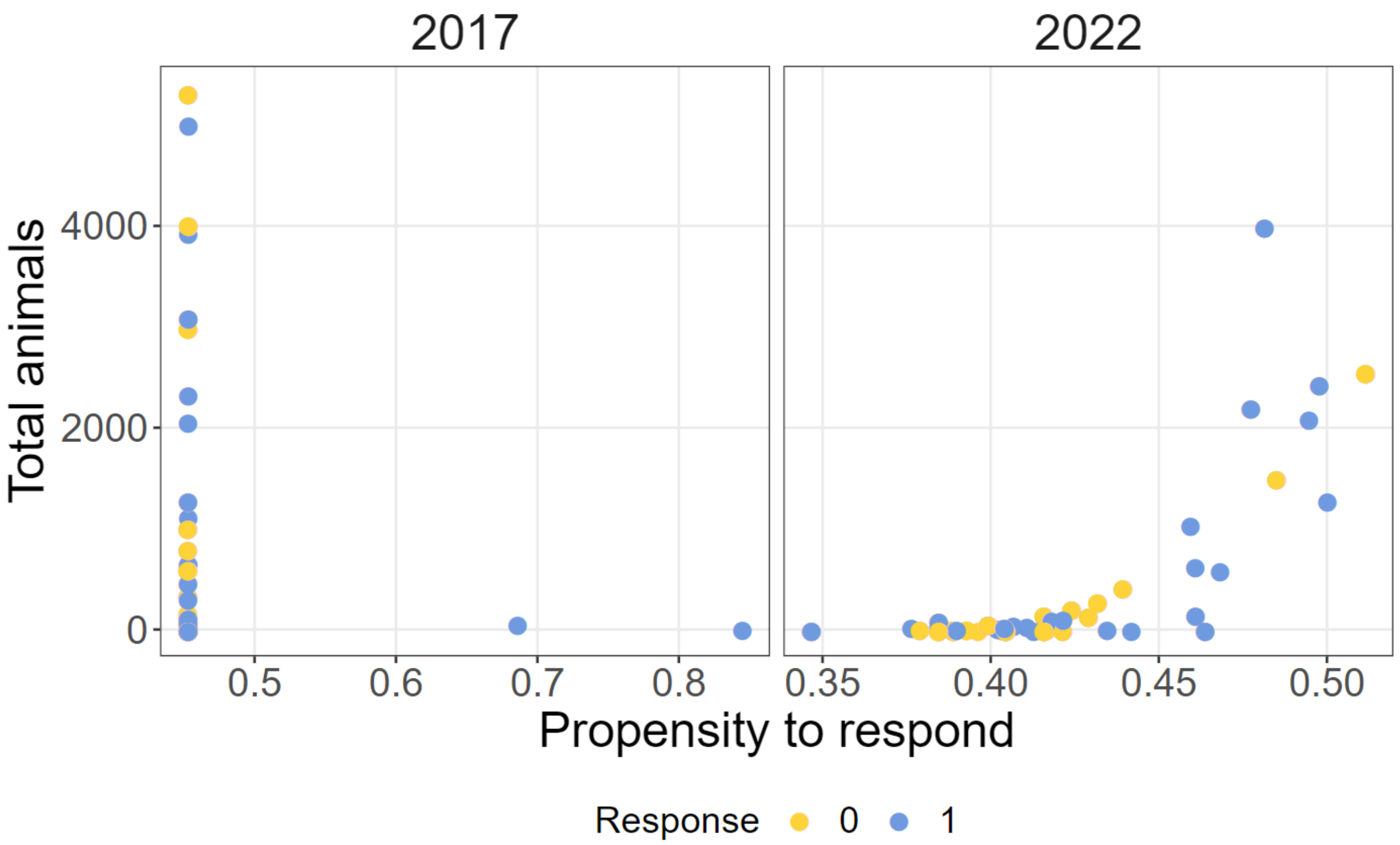


Bias within imputation cells



- Poststratification and imputation will reduce nonresponse bias if response propensities are homogeneous within strata
- And if there is little correlation between response propensities and the response variable

Bias within imputation cells



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Response propensity weight adjustment

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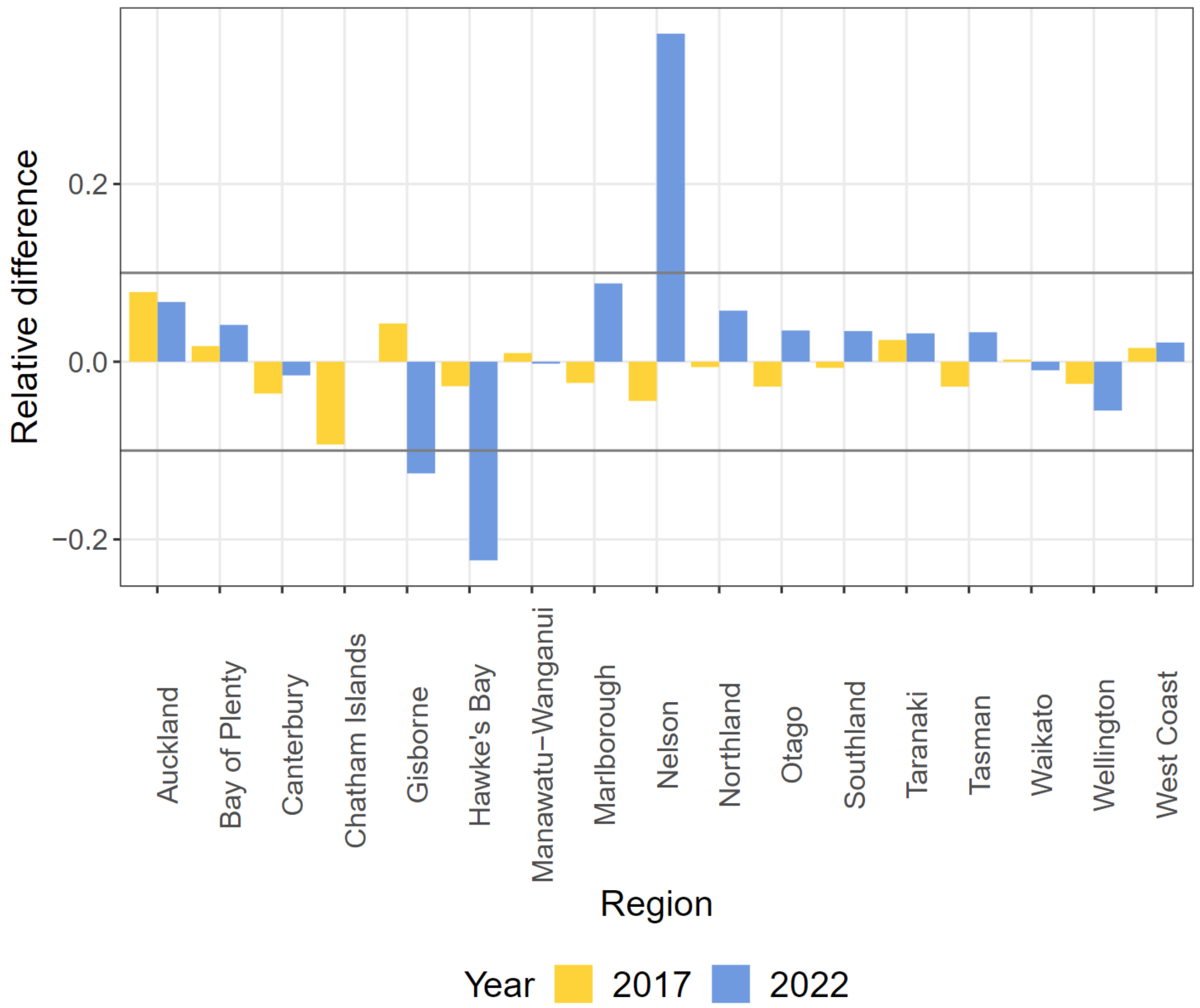
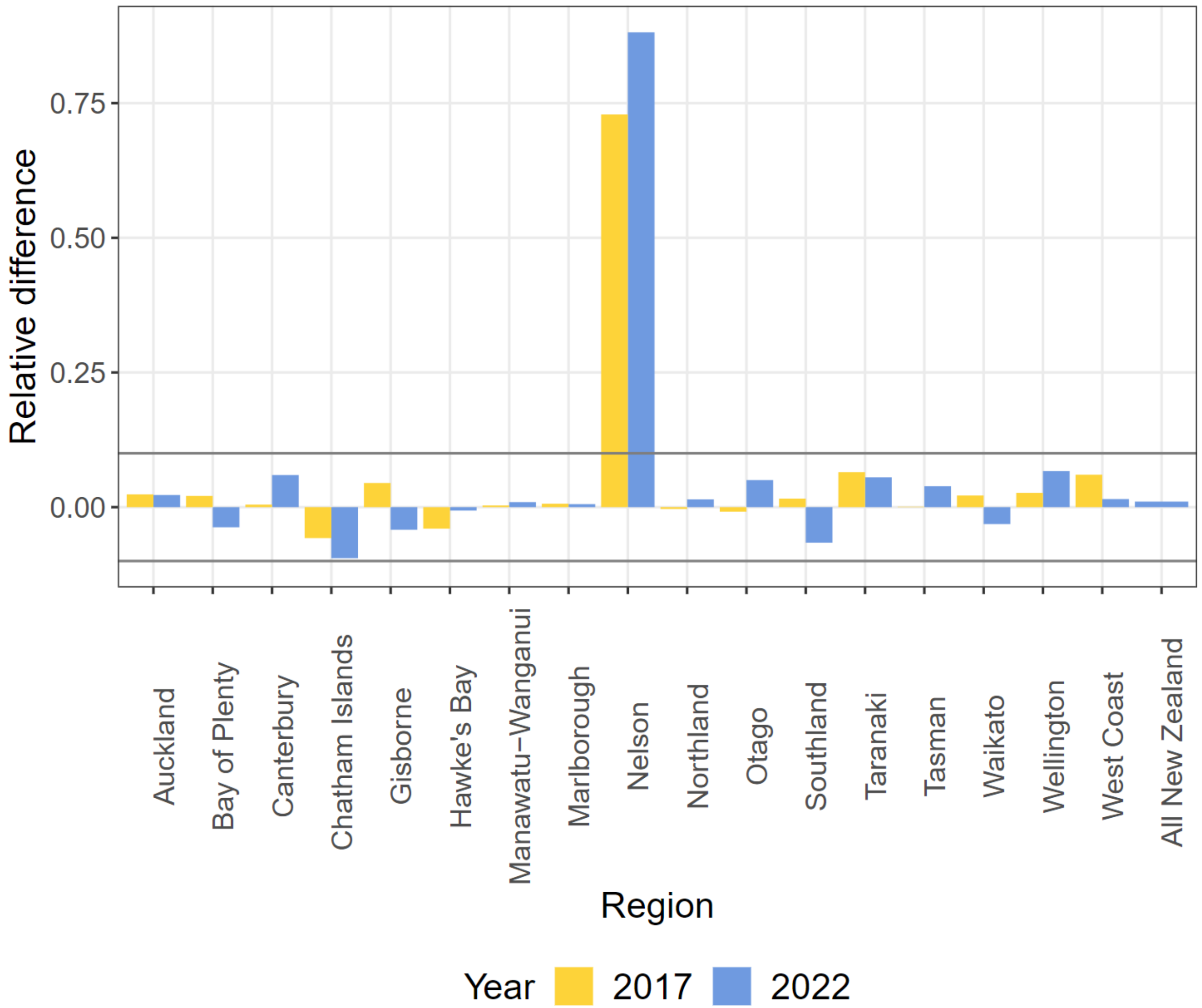


- Comparison between donor imputation and response propensity weight adjustment
- Dairy cows

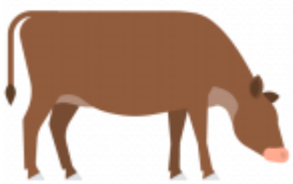
Response propensity weight adjustment



- Beef cows

Main findings

- Main predictors of response propensity were size of the farm and the number of past responses.
- Response propensities decreased from 2017 to 2022 and were more widespread in 2022
- However, the patterns of response propensity remained similar to those observed in 2017
- For some imputation cells in 2022 response propensities were not homogeneous per strata and covaried with the number of animals, which likely introduced nonresponse bias at this level.
- At a regional level the results of the donor imputation and response propensity weighting methods were consistent



Moving forward

- Predicting response propensities is increasingly important to understand nonresponse bias. New covariates and predictive models can and should be explored if we want to accurately quantify nonresponse bias.
- As for the current release:
  - Some cells were divided to make them more homogeneous.
  - Suppression of outputs that derive from a high percentage of biased cells
- For future estimates:
  - New imputation methods can and should be explored under the assumption that response rates might not improve.
  - Multiple imputation
  - Weight calibration methods with response propensity
  - Model assisted estimates.

Thank you

Nonresponse bias

$$bias(\hat{y^{pst}}) \approx N^{-1} \sum \bar{\phi_h}^{-1} \sigma_{\phi_h} \sigma_{Y_h} \rho_{\phi_h, Yh}$$

- $\hat{y}^0$ estimated mean of the postratified estimator
- h denotes stratification classes

- Poststratification will reduce non response bias if the distributions of ϕ or Y are less variable within post strata than across post strata
- Or if their covariance is attenuated within post strata
- A good choice for a post stratification variable would be a variable highly correlated with the response propensities such that response propensities were constant with each level
- The total nonresponse bias is the sum of bias across all strata

Brick, J. M. (2013). Unit nonresponse and weighting adjustments: A critical review. *Journal of Official Statistics*, *29*(3), 329-353.

Nonresponse bias

$$bias(\hat{\bar{y}}^0) = \bar{\phi}^{-1}\sigma_\phi \sigma_Y \rho_{\phi,Y}$$

- $\hat{\bar{y}}^0$ The unadjusted estimator of the respondents mean
- $\bar{\phi}^{-1}$ The population mean of response propensities
- σ_ϕ The standard deviation of response propensities
- σ_Y The standard deviation of the response variable
- $\rho_{\phi,Y}$ The correlation between response propensity and the response variable

- Stochastic representation of bias.
- It assumes that response is a random variable and the probability of response is like the probability in an additional phase of sampling
- However the probability for every unit in this phase is unknown, thus has to be *estimated.*
- The estimated respondent mean is unbiased if $\rho = 0$.

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Nonresponse bias of the total

$$bias(\hat{y}^{pst}) \approx \sum_h \bar{\phi}_h^{-1} \sum_i Y_{hi}(\phi_{hi} - \bar{\phi}_h)$$

- Different estimators have different expressions of bias.
- The total bias of the estimate is the sum across all strata
- Imputation allows us to have Y values for respondents and nonrespondents

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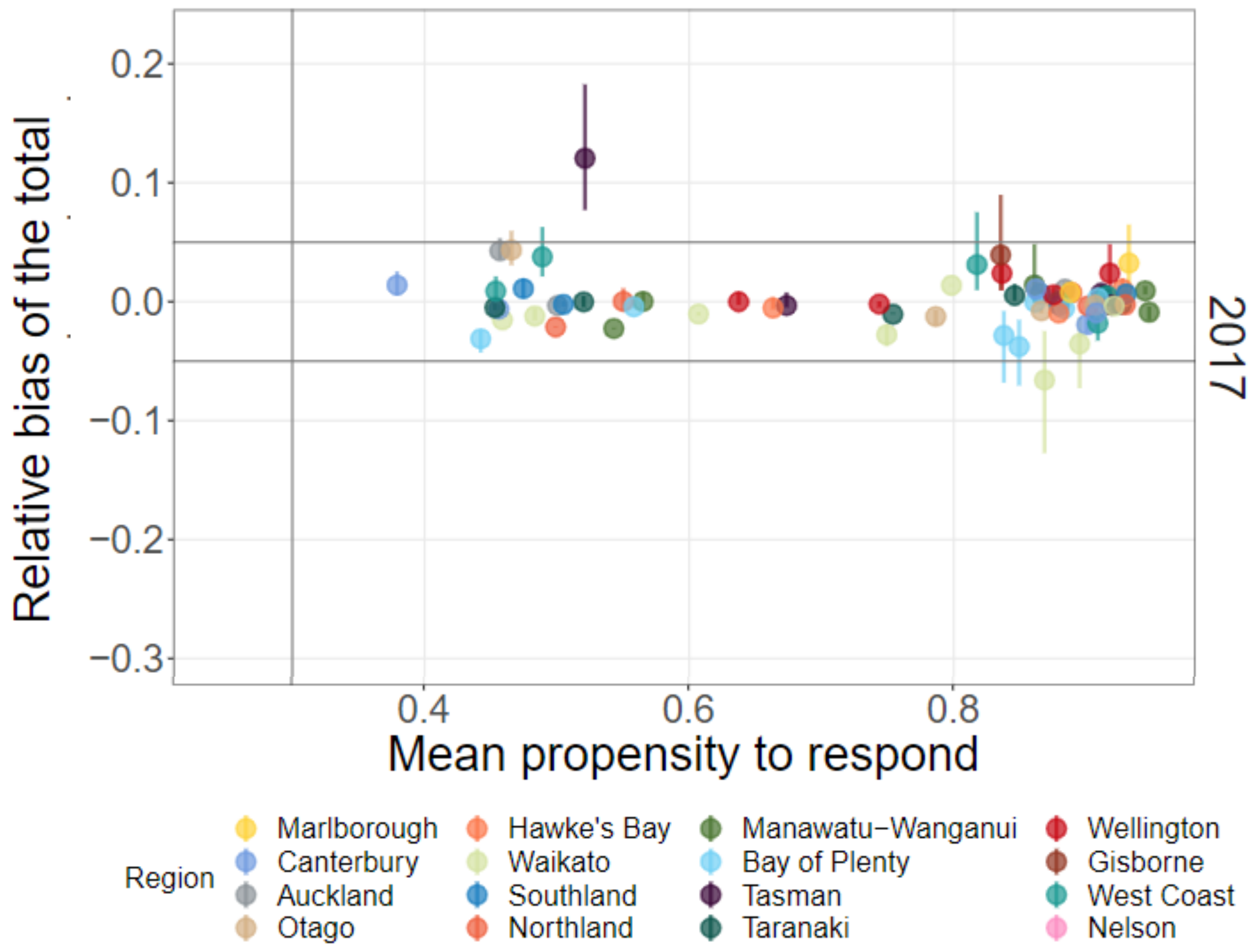
- Types of data that can produce estimates of nonresponse bias
  - Sample frame data (i.e., where records were available both on respondents and nonrespondents)
  - Supplemental data for both respondents and nonrespondents, linked to the sample data.
  - Follow up studies of nonrespondents, comparing the earlier respondent group to those former respondents
  - Reports of intentions to respond to a later survey, comparing those who report agreeing to respond with those who decline to respond
  - Screener interview data

Groves, R. M., & Peytcheva, E. (2008). The impact of nonresponse rates on nonresponse bias: a meta-analysis. *Public opinion quarterly*, *72*(2), 167-189.

Imputation cells

- The same variables used for forming selection cells are used to form imputation cells (region, farm type and farm size)
- With some minor adjustments for merging small cells
- Farm size is an imputation variable which strongly correlates with key response variables.
- For each nonrespondent the values for all variables to be imputed are copied from the next available donor in the cell
- Each unit can only be used as a donor up to 6 times
- Unlinking may occur
- Key farms are not imputed via donor imputation but by using past information
- If groups are homogeneous imputation will work.

Bias across imputation cells – Dairy cows



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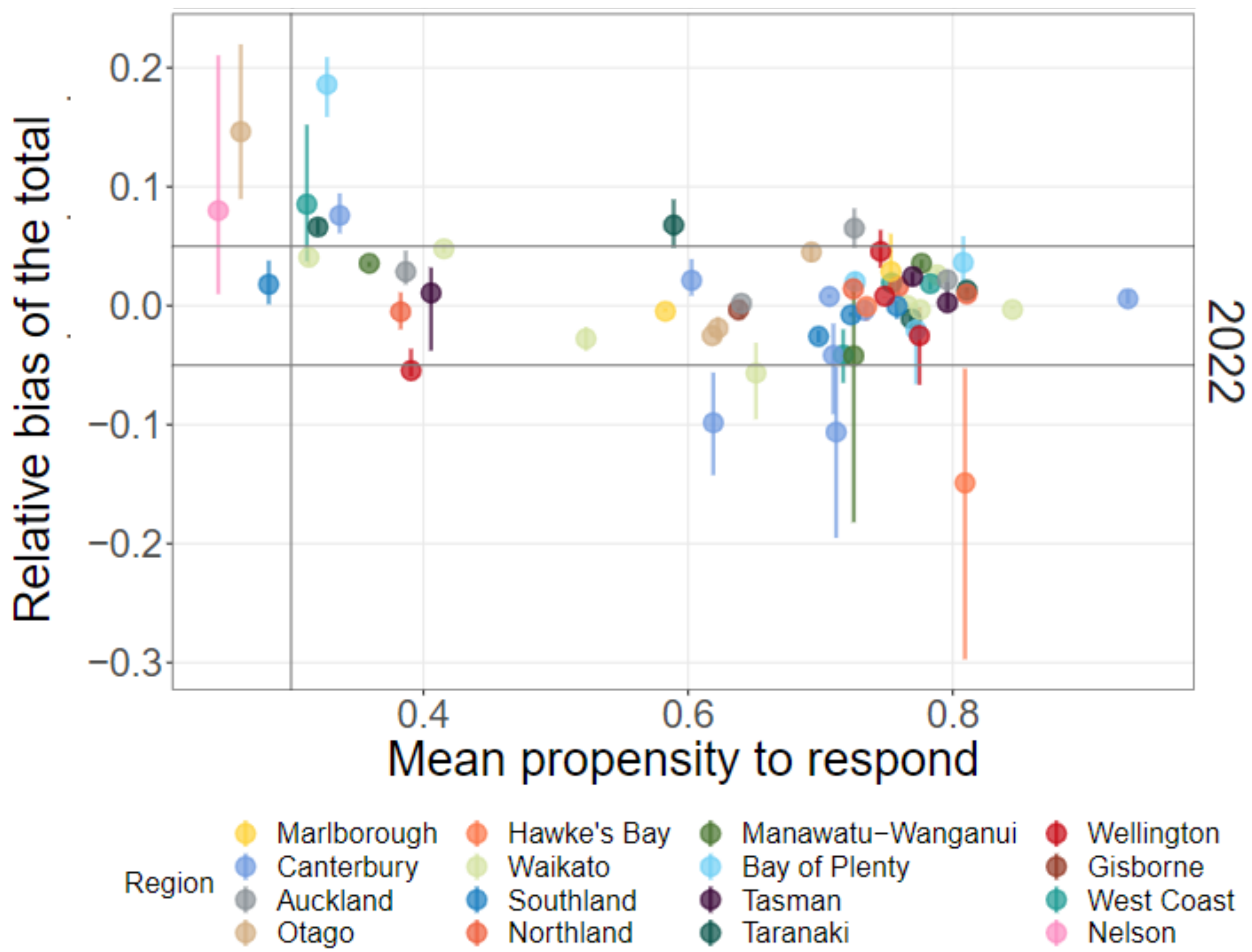

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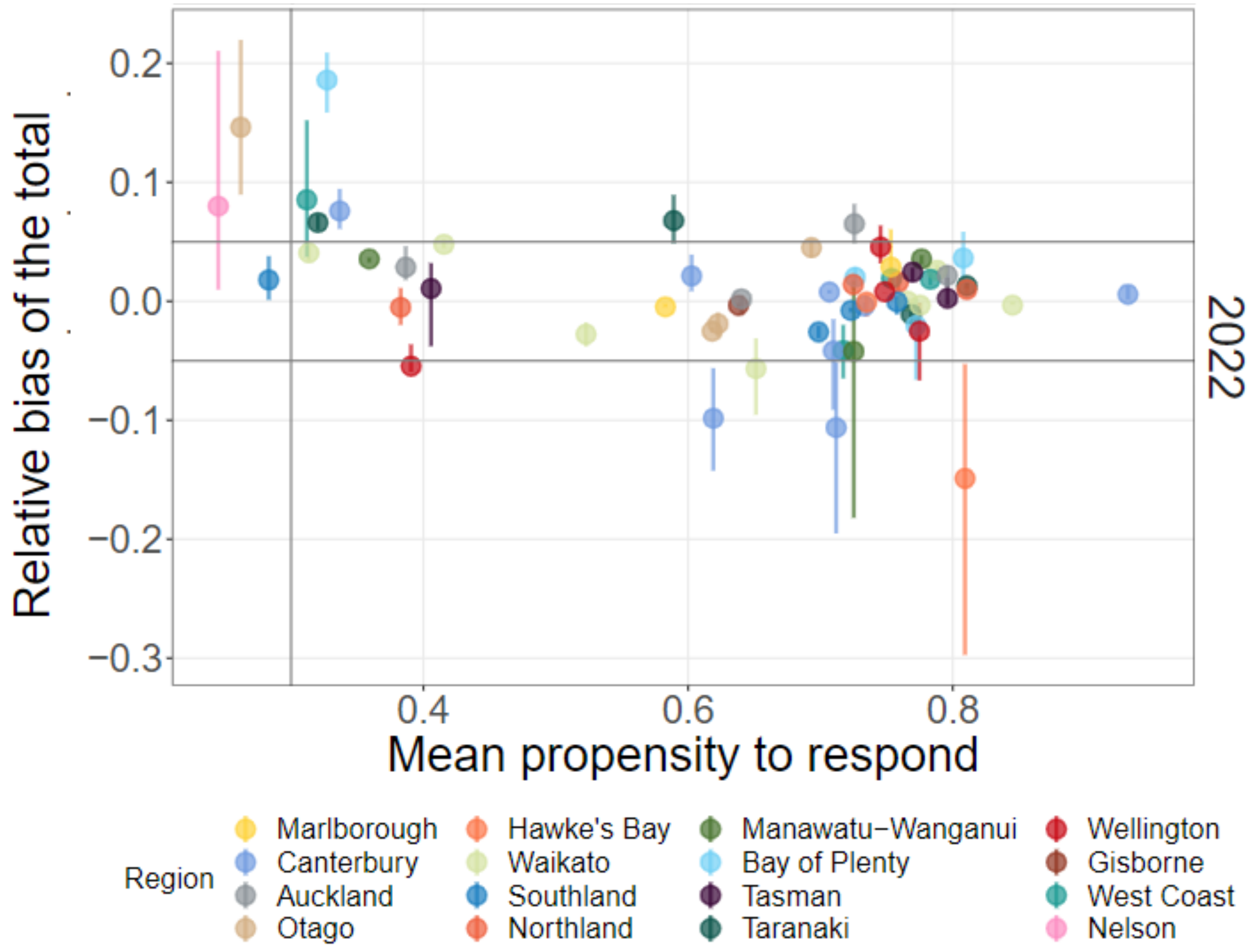
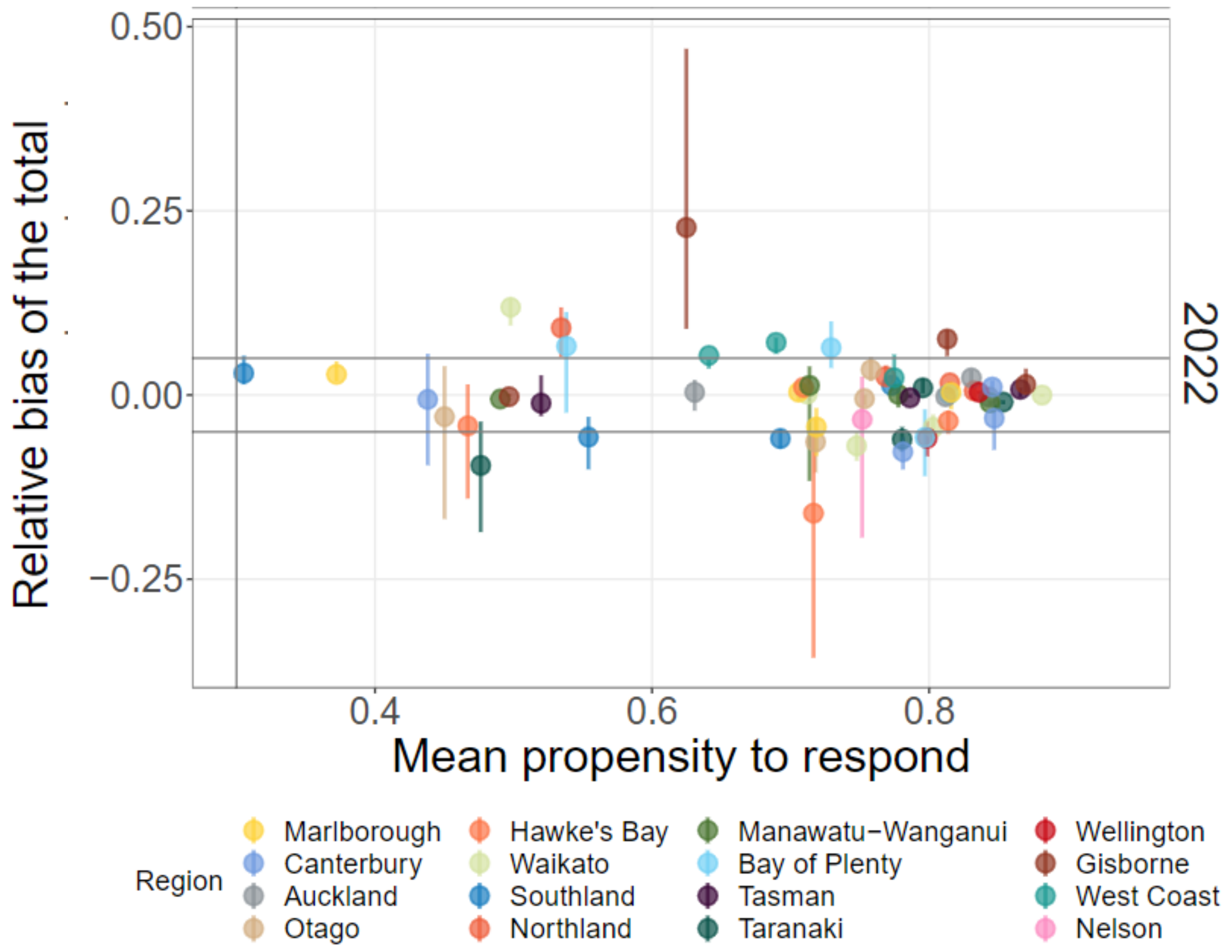


Bias across imputation cells – Beef cows



Thank you