The Geography of Nonresponse

Can spatial econometric techniques improve survey weights for nonresponse?

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Background & Motivation

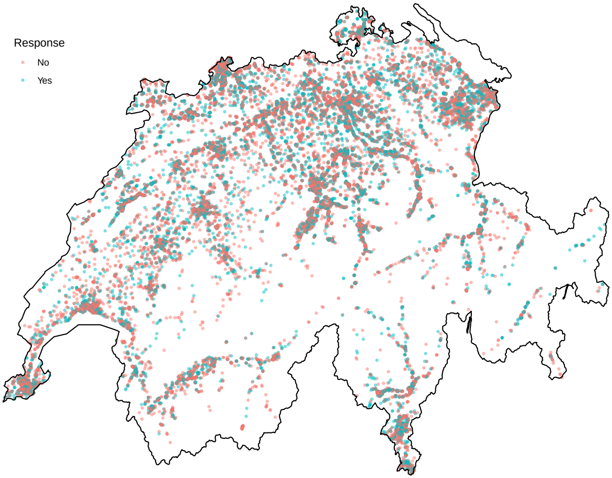

Figure 1: Nonresponse a national survey in Switzerland, 2018 (N ≈ 25'900)

Non-response is geographically clustered

Reason:

Segregation

- Different people end up in different geographical contexts
- (Budget) constraints (Clark and Lisowski, 2017; Schaake, Burgers, and Mulder, 2014)
- Housing preferences (Bruch and Mare, 2006; Ibraimovic and Hess, 2018)
- Discrimination (Ahmed and Hammarstedt, 2008; Auspurg, Hinz, and Schmid, 2017)

Existing research

- GIS for mapping patterns of nonresponse (Hansen et al., 2007)
- Identification of geographic areas with hard to reach segments of the population (Low Response Score – Abbott and Compton, 2014; Erdman and Bates, 2017)
- Geocoded census characteristics as aggregated paradata for weighting survey response (Biemer and Peytchev, 2013; Olson, 2013)

$\Rightarrow$ Why not make use of the spatial dependence more directly?!

$\Rightarrow$ **Idea: Nearby units' response status as a predictor for a particular unit's response status**

$\Rightarrow$ Spatial Econometric models

Response probabilities

Response probabilities SAR (probit case):

$$\begin{aligned}\phi_i(\boldsymbol{x}_i) &= p\left(\left[(\mathbb{I}-\rho\mathbf{W})^{-1}\boldsymbol{X}\boldsymbol{\beta}\right]_i + \left[(\mathbb{I}-\rho\mathbf{W})^{-1}\boldsymbol{\varepsilon}\right]_i > 0\right) \\ &= \Phi\left\{\left[(\mathbb{I}-\rho\mathbf{W})^{-1}\boldsymbol{X}\boldsymbol{\beta}\right]/\sigma_u\right\},\end{aligned} \tag{1}$$

where $u = (\mathbb{I}-\rho\mathbf{W})^{-1}\boldsymbol{\varepsilon}$.

SEM (probit case):

$$\phi_i(\boldsymbol{x}_i) = \Phi\left\{\boldsymbol{X}\boldsymbol{\beta}/\sigma_u\right\} \tag{2}$$

Inverse probability weights:

$$\omega_i = \frac{1}{\phi_i(\boldsymbol{x}_i)} \tag{3}$$

$\Rightarrow$ e.g., weighted average: $\bar{y} = (\sum_{i=1}^n y_i\omega_i)/\sum_{i=1}^n \omega_i$

How to proceed?

Model estimation

Predict response probabilities with:

- $oX1$ and $oX2$
- aggregated paradata $u\bar{X}1$ (e.g., share of people with tertiary degree in census districts)
- different models:
  - GLM
  - SEM
  - SAR
  - GLMM
  - SEM with paradata
  - SAR with paradata

Simulation

DGP

$$\boldsymbol{\phi}(\boldsymbol{X}) \sim Bin(1, \pi), \quad \pi = \frac{\exp(\mathbf{X}\boldsymbol{\beta})}{(1 + \exp(\mathbf{X}\boldsymbol{\beta}))}, \text{ where} \tag{4}$$

$$\boldsymbol{X} = \begin{pmatrix} 1^T & uX_1 & oX_1 & oX_2 \end{pmatrix},$$

$$uX_1 \sim (\mathbb{I} - \rho\mathbf{W})^{-1} \times Bin(5, 0.2),$$

$$oX_1 \sim (\mathbb{I} - \rho\mathbf{W})^{-1} \times Bin(1, 0.01), \quad oX_2 = Bin(3, 0.4)$$

$$\boldsymbol{\beta} = \begin{pmatrix} \boldsymbol{\beta}_0 & 1.7 & -2.5 & -2.5 \end{pmatrix}^T, \boldsymbol{\beta}_0 = \{-1.8, -2.0, -2.2\}, \quad \rho = \{0.4, 0.5, 0.6\}$$

$$cov(uX1, oX1) = -0.2$$

Evaluating estimator performance: Outcome measure

Weighted average outcome $\hat{\bar{y}}$

$$
\begin{aligned}
y_i &\sim N(\mu_y, \sigma_y), \\
\mu_y &= 3000 + \overbrace{\underbrace{300 \times uX_1}_{sp.cor.}}^{\text{unobs.}} - \overbrace{\underbrace{950 \times oX_1}_{sp.cor.} + 200 \times oX_2}^{obs.} \qquad (5) \\
\sigma_y &= 300
\end{aligned}
$$

Look at the MSE of $\hat{\bar{y}}$:

$$MSE_y = \mathbb{E}\left[\left(\hat{\bar{y}} - \bar{Y}\right)^2\right] = \mathbb{E}\left[\left(\hat{\bar{y}} - \mathbb{E}\left[\hat{\bar{y}}\right]\right)^2\right] + \left(\mathbb{E}\left[\hat{\bar{y}}\right] - \bar{Y}\right)^2 \tag{6}$$

Main Scenarios

- 3 values of ρ
- 2 different geographic resolutions (25 vs. 100 subgrids)
- 6 different types of models (GLM, SEM, SAR, GLMM, SEM with aggregated characteristic, SAR with aggregated characteristic)
- 1000 observations
- 1000 replications

$\Rightarrow 3 \times 2 \times 6 \times 1000 = 36'000$ models ($\times 3 \times 3$ for different *cov* matrix and different response prob.)

Robustness

- ✓ Change response rate:
  40 vs. 50 vs. 60 percent
- ✓ Change covariance structure among independent variables:
  off-diagonal elements -0.2 vs. -0.35 vs. -0.5
- ✓ Varying amount of weight-trimming:
  max. weight 99% vs. 95% vs. 90% quantile
- ✗ Misspecify weights matrix

What does the «world» look like?

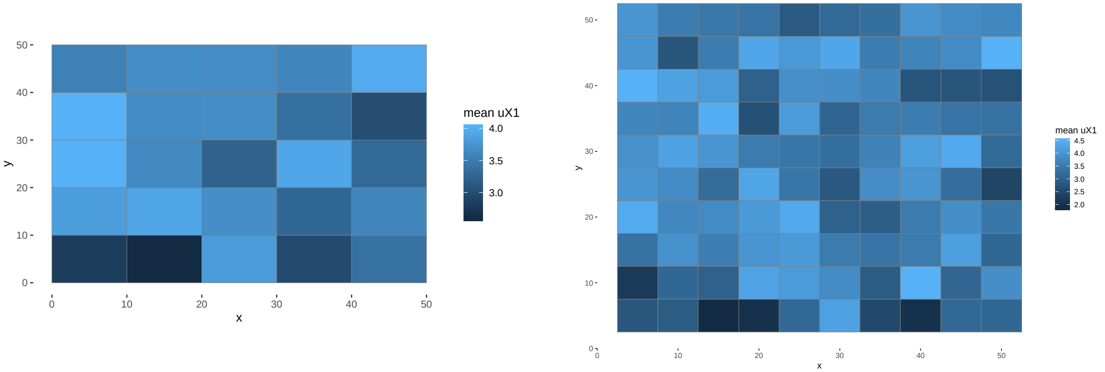

Figure 2: Average $uX1$ in the artificial world

1. Spatial Dependence

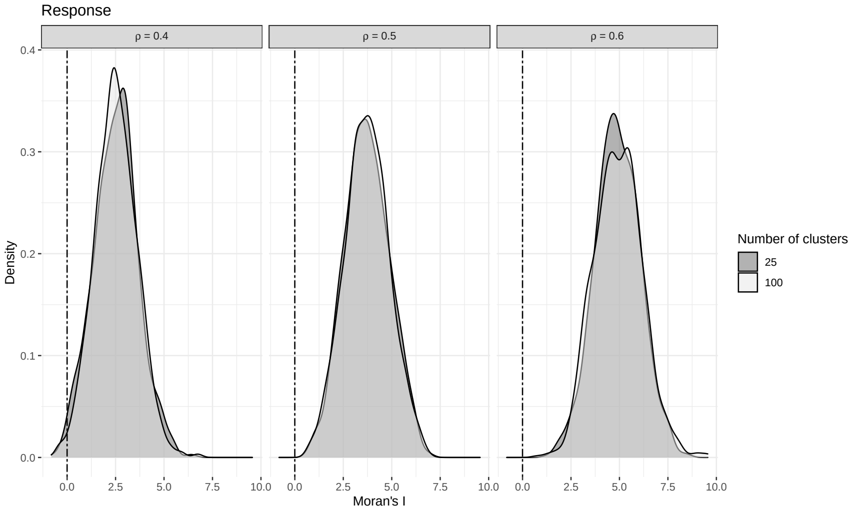

Figure 3: Moran's I: Response

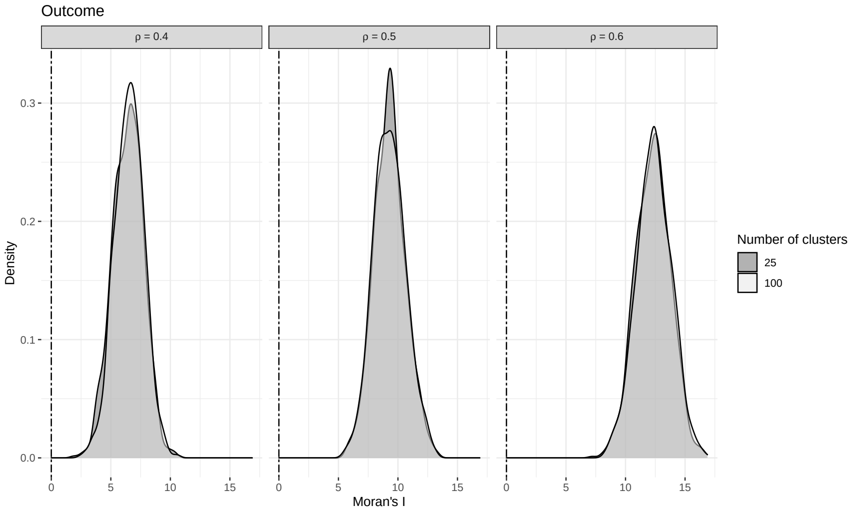

Figure 4: Moran's I: Outcome

2. Model Performance

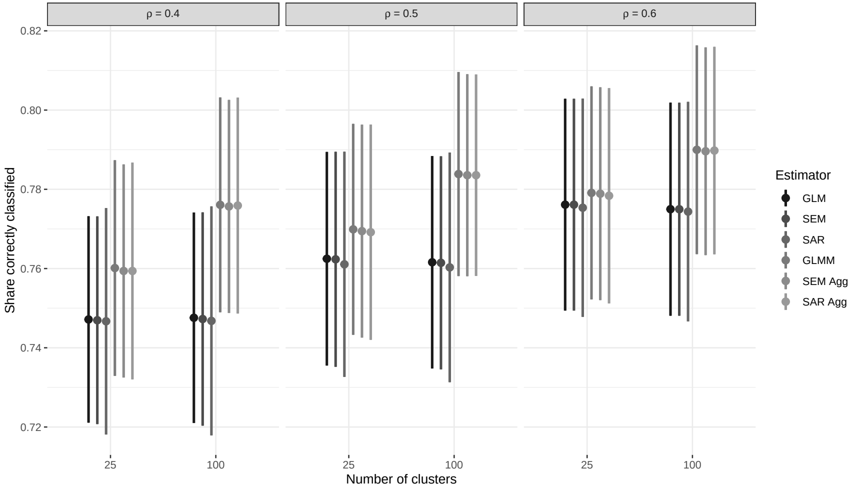

Figure 5: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.4,\ cov(uX1, oX1) = -0.2$, Pseudo $R^2 \approx 0.25$

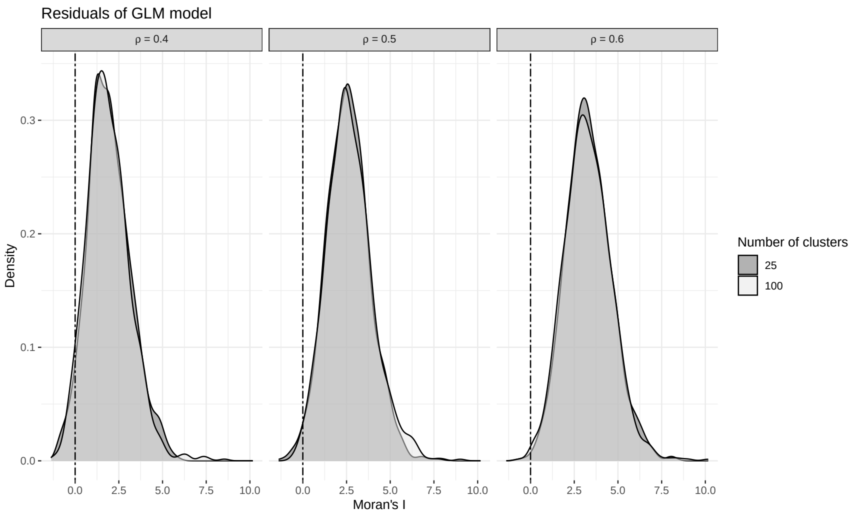

Figure 6: Moran's I: GLM Residuals

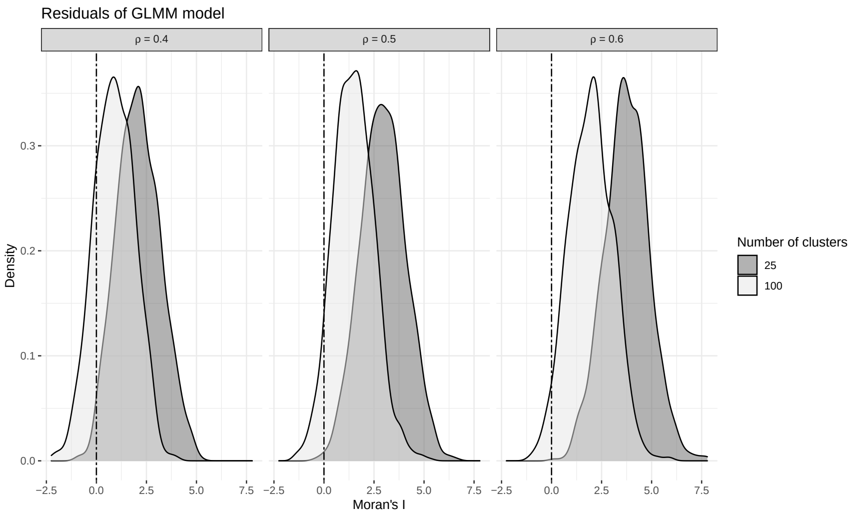

Figure 7: Moran's I: GLMM Residuals

3.1. Weight trimming

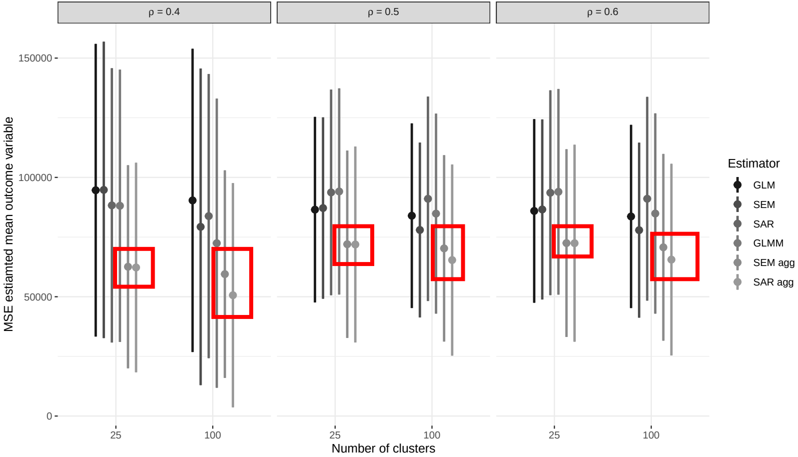

Figure 8: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.4$, $cov(uX1, oX1) = -0.2$, max. weight: 99% quantile

3.1. Weight trimming

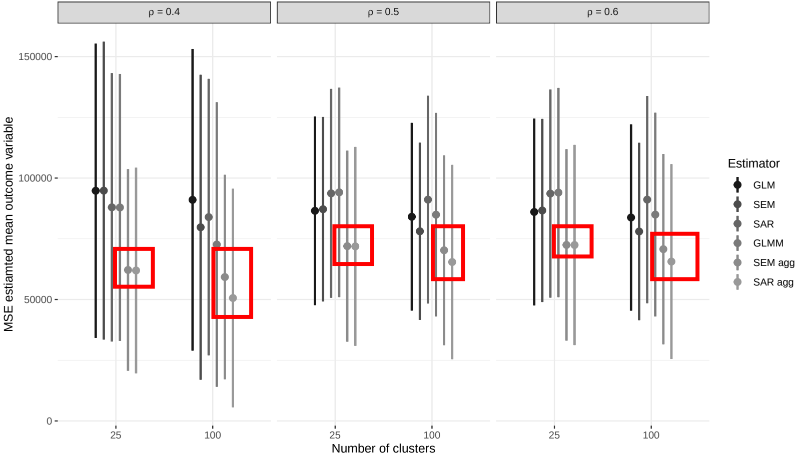

Figure 8: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.4$, $cov(uX1, oX1) = -0.2$, max. weight: 95% quantile

3.1. Weight trimming

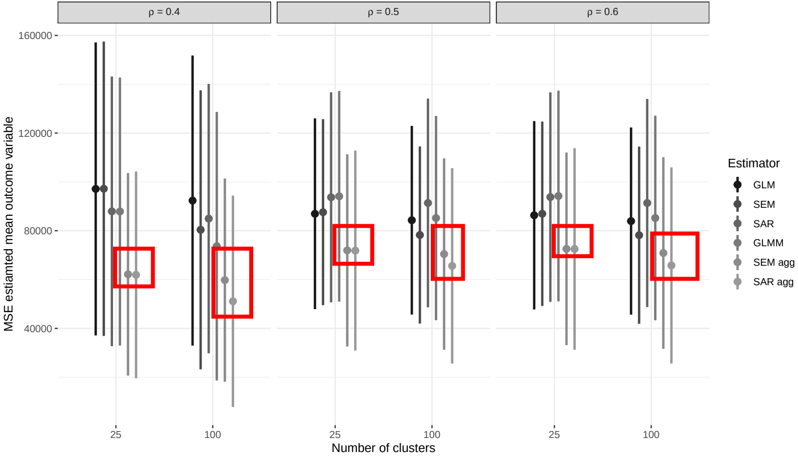

Figure 8: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.4$, $cov(uX1, oX1) = -0.2$, max. weight: 90% quantile

Conclusion

- Nonresponse is often geographically dependent
  - due to unobserved selection processes ...
  - ... rather than a contagious behavior
  - Nevertheless: Treat as if contagious to incorporate others' response status
- Incorporating response of neighboring units increases accuracy of $\hat{\phi}_i$, even in the presence of omitted variable bias
- Especially if large weights are trimmed
- However:
  - Advantages only if spatial models pick up residual spatial correlation after accounting for higher level variance
  - Depends on underlying spatial association, response propensity, and covariance structure

Open topics

- Misspecified weights matrix
- Association of outcome measure with spatial process
- Real-world benchmark
- Vary power of prediction model

Thanks for the attention!

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Appendix

Idea

Make use of spatial dependence in non-response.
Two models to consider:

$$\boldsymbol{Y}^* = \rho \boldsymbol{W}\boldsymbol{Y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \quad \boldsymbol{\varepsilon} \sim \mathcal{N}(0, \sigma^2 \mathbb{I}) \tag{7a}$$

$$\Leftrightarrow \qquad \boldsymbol{Y}^* = (\mathbb{I} - \rho \boldsymbol{W})^{-1}(\boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}) \tag{7b}$$

Spatial Lag Model (SAR)

$$\boldsymbol{Y}^* = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\nu}, \quad \boldsymbol{\nu} = \lambda \boldsymbol{W}\boldsymbol{\nu} + \boldsymbol{\varepsilon}, \quad \boldsymbol{\varepsilon} \sim \mathcal{N}(0, \sigma^2 \mathbb{I}) \tag{8a}$$

$$\Leftrightarrow \qquad \boldsymbol{Y}^* = \boldsymbol{X}\boldsymbol{\beta} + (\mathbb{I} - \gamma \boldsymbol{W})^{-1}\boldsymbol{\varepsilon} \tag{8b}$$

Spatial Error Model (SEM)

What does the «world» look like?

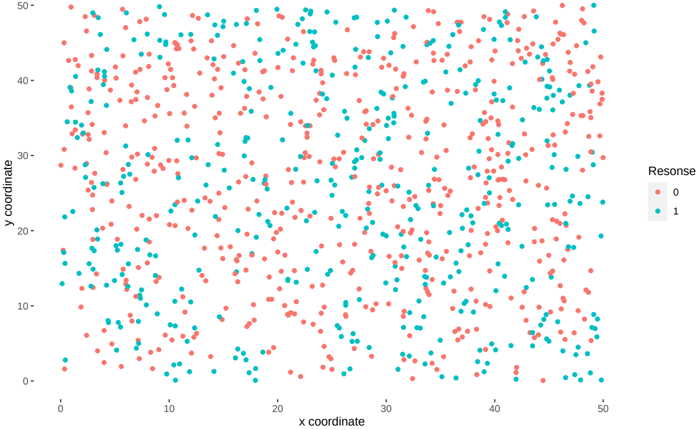

Figure A.1: Example distribution of response in simulated data

3.2. Response rate

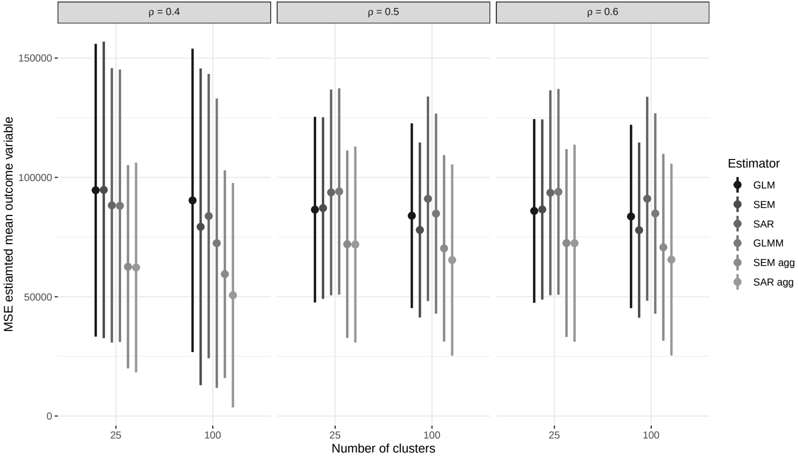

Figure A.2: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.4$, $cov(uX1, oX1) = -0.2$, max. weight: 99% quantile

3.2. Response rate

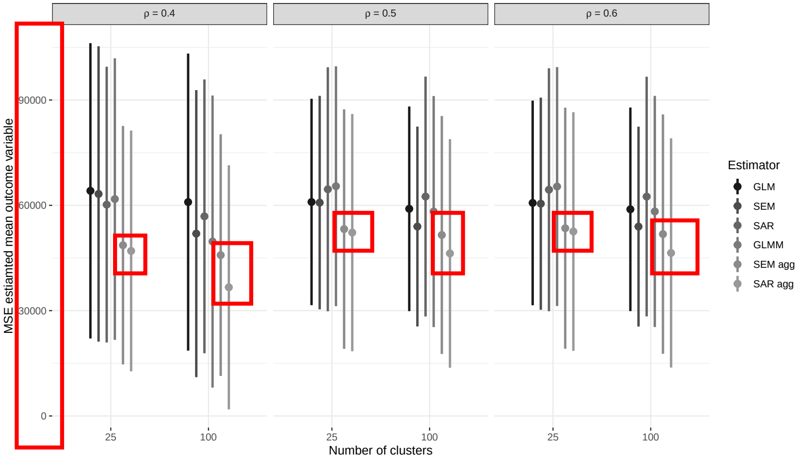

Figure A.2: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5$, $cov(uX1, oX1) = -0.2$, max. weight: 99% quantile

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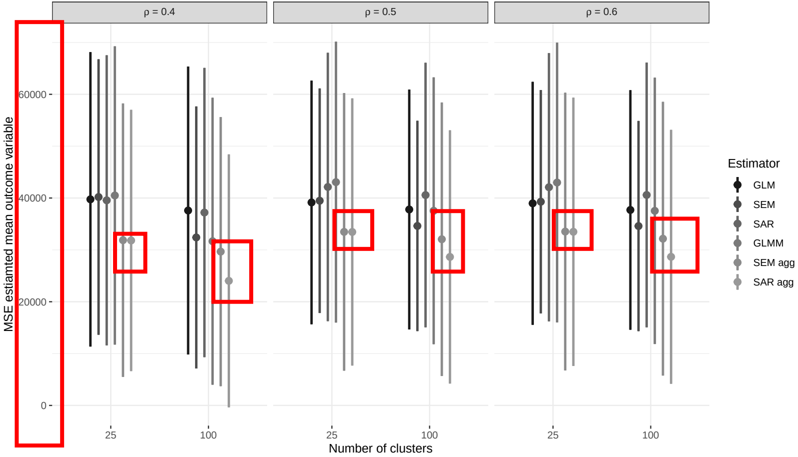

Figure A.2: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6$, $cov(uX1, oX1) = -0.2$, max. weight: 99% quantile

3.3. Covariance Structure

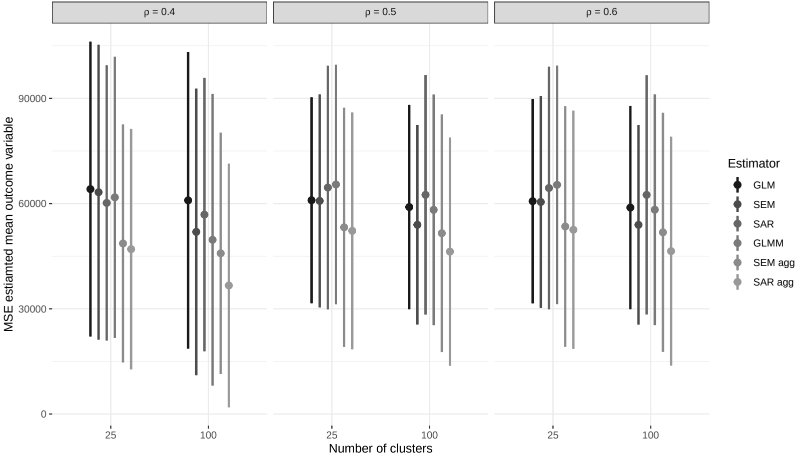

Figure A.3: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5$, $cov(uX1, oX1) = 0.2$, max. weight: 99% quantile

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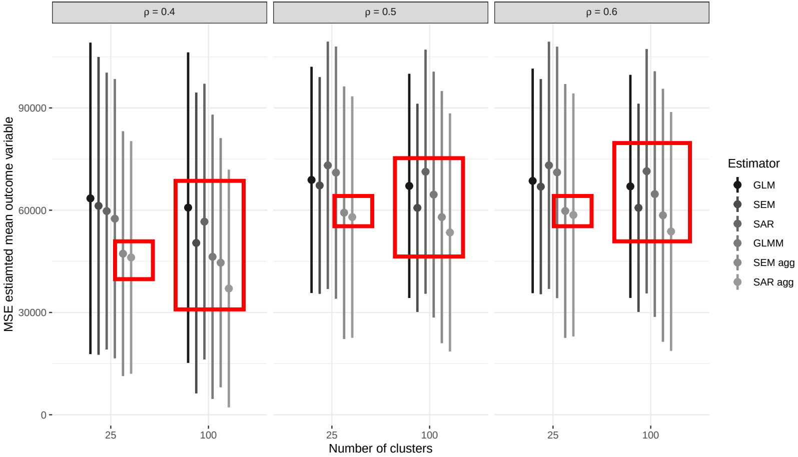

Figure A.3: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5$, $cov(uX1, oX1) = -0.35$, max. weight: 99% quantile

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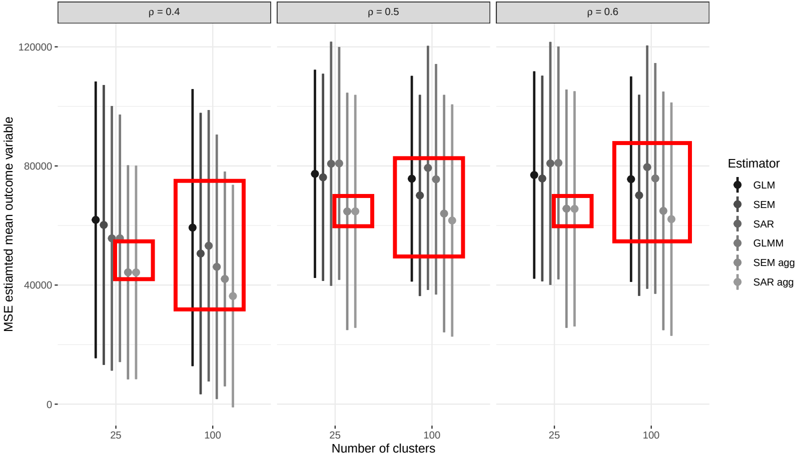

Figure A.3: MSE trimmed weighted average outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5$, $cov(uX1, oX1) = -0.50$, max. weight: 99% quantile

Spatial Dependence

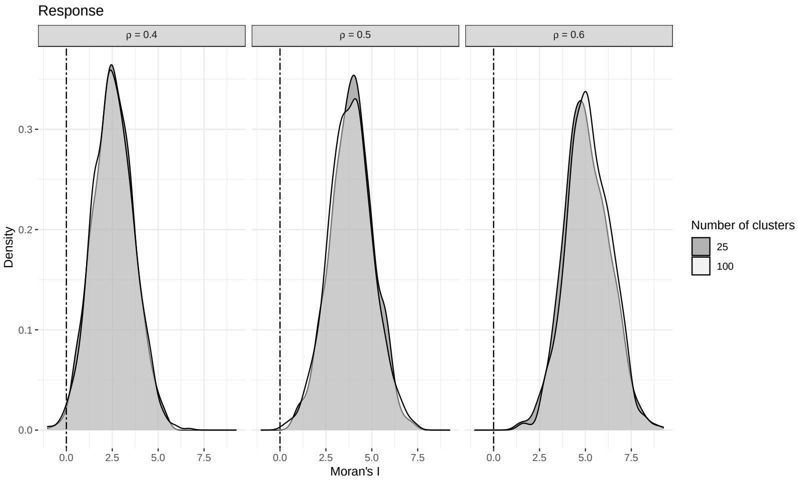

Figure A.4: Moran's I Response $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20$

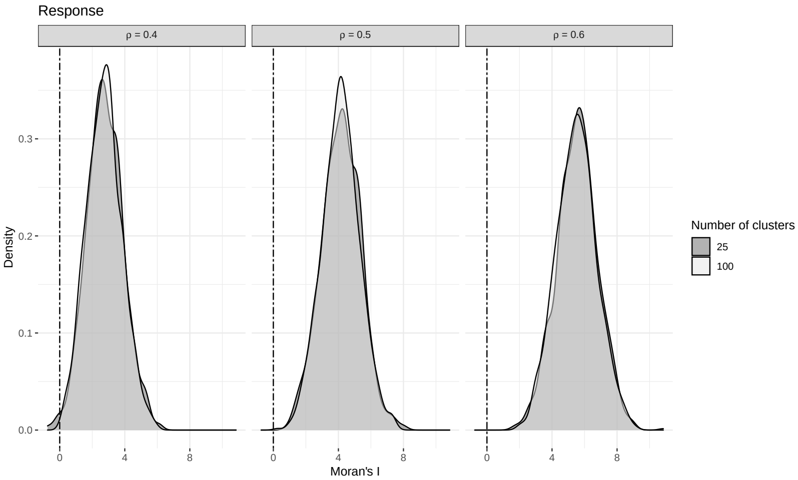

Figure A.5: Moran's I Response $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35$

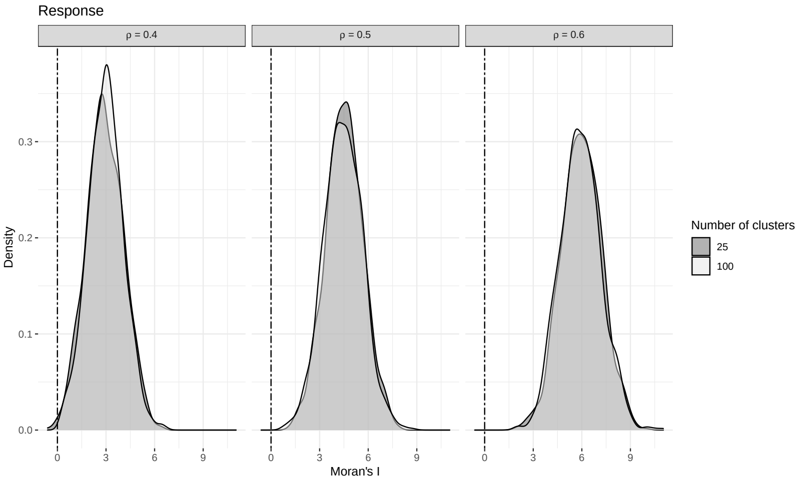

Figure A.6: Moran's I Response $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50$

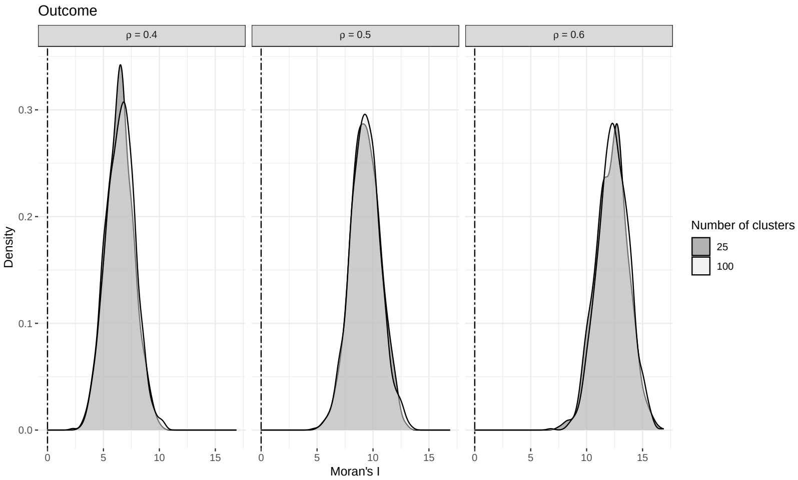

Figure A.7: Moran's I Outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20$

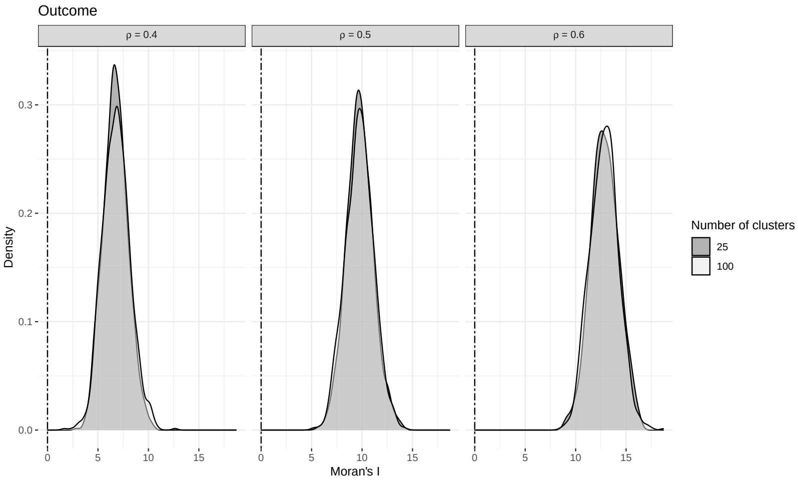

Figure A.8: Moran's I Outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35$

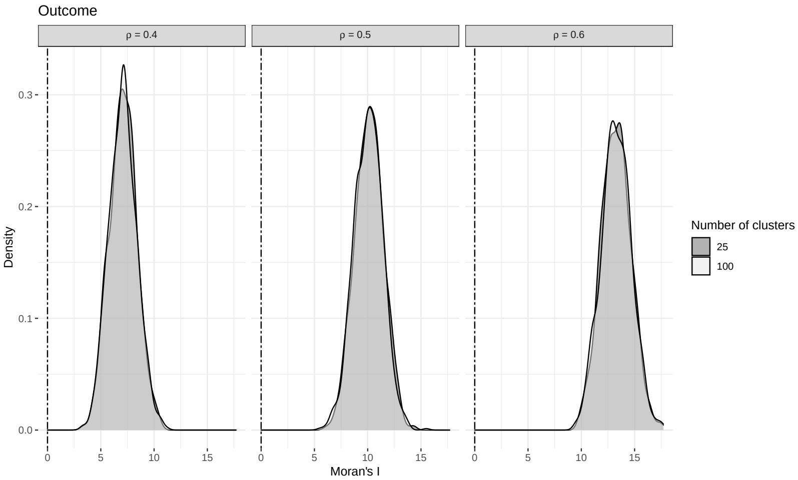

Figure A.9: Moran's I Outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50$

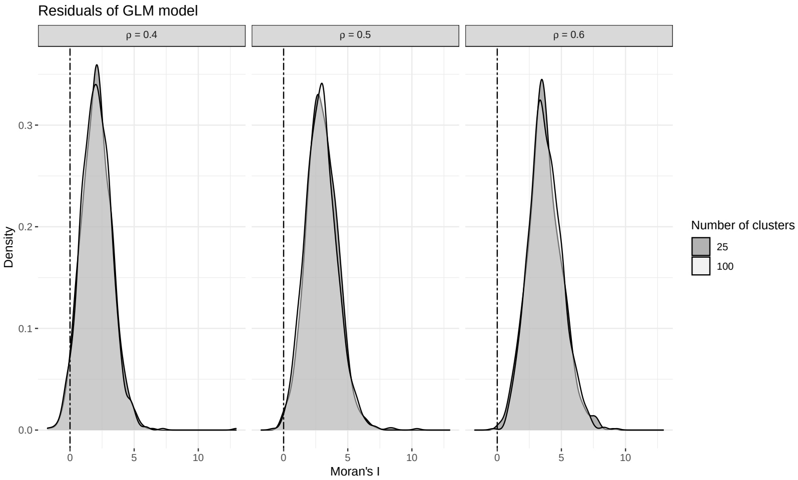

Figure A.10: Moran's I GLM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20$

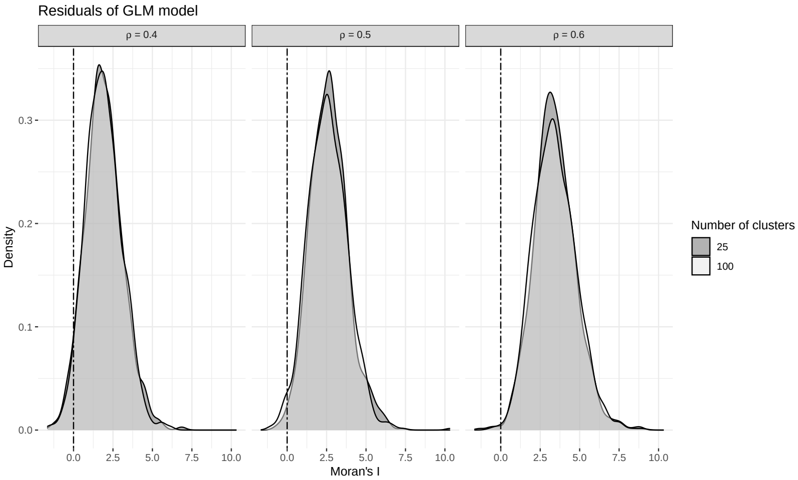

Figure A.11: Moran's I GLM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35$

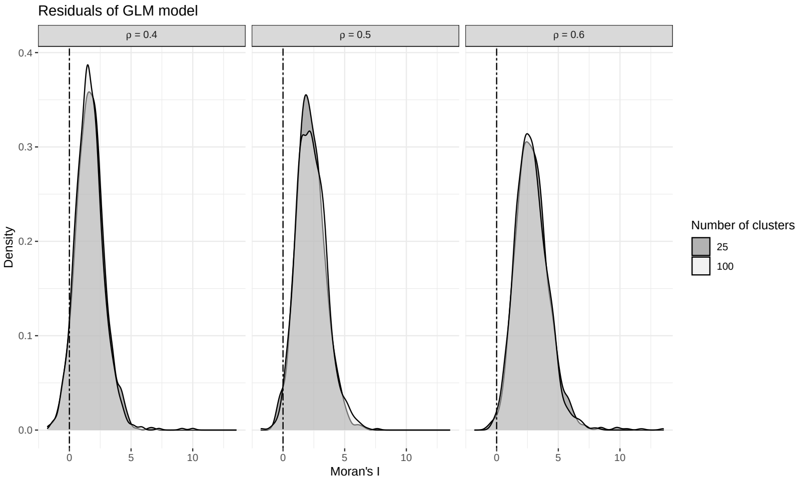

Figure A.12: Moran's I GLM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50$

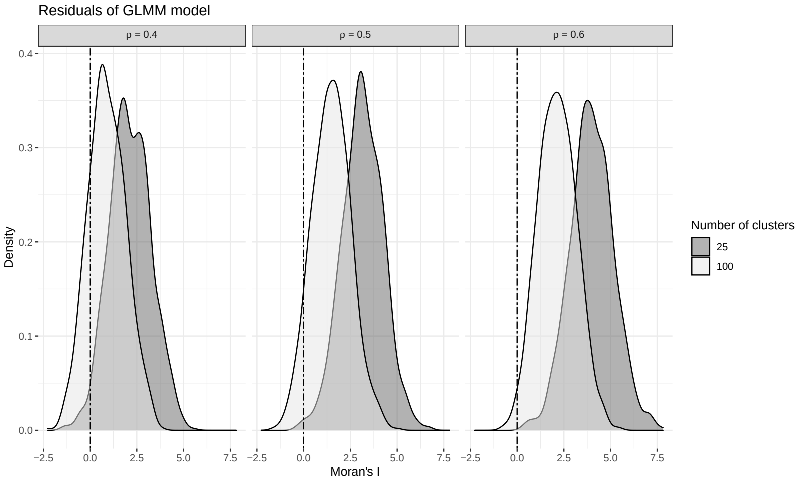

Figure A.13: Moran's I GLMM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20$

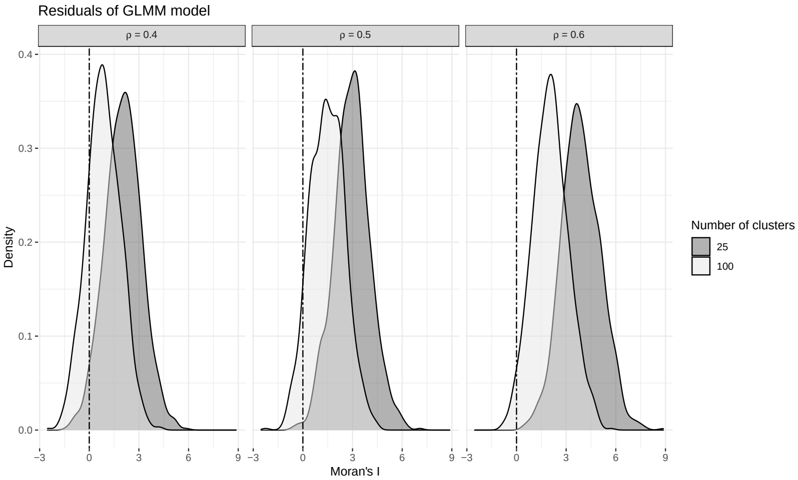

Figure A.14: Moran's I GLMM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35$

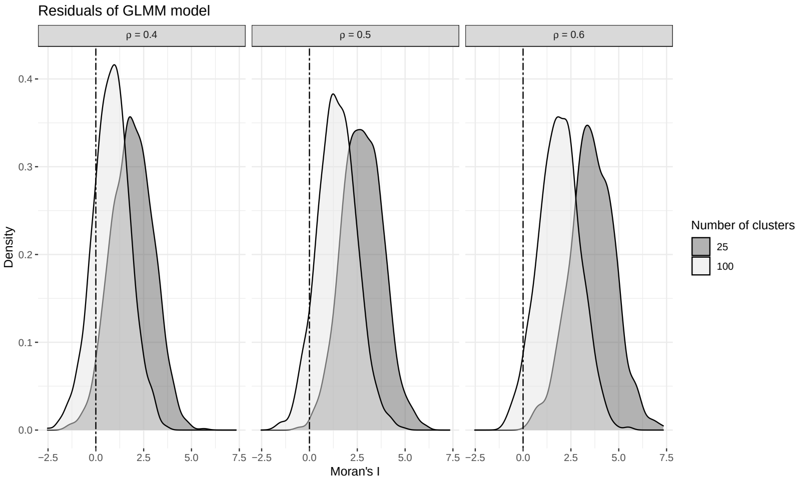

Figure A.15: Moran's I GLMM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50$

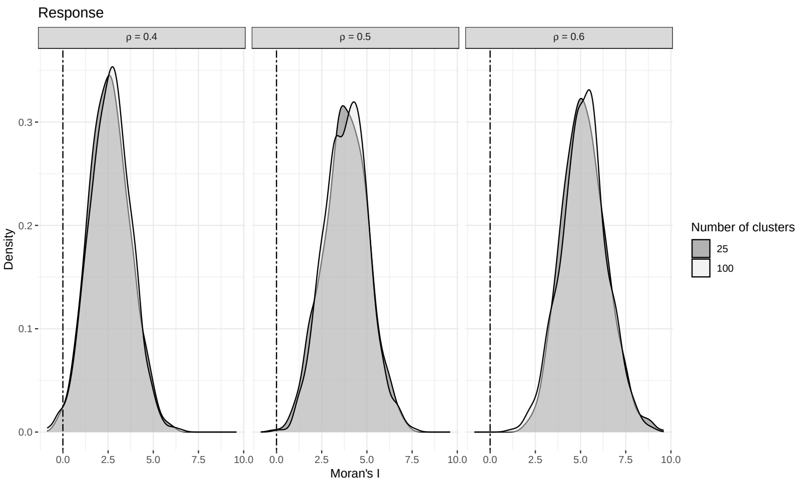

Figure A.16: Moran's I Response $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6, \; cov(uX1, oX1) = 0.20$

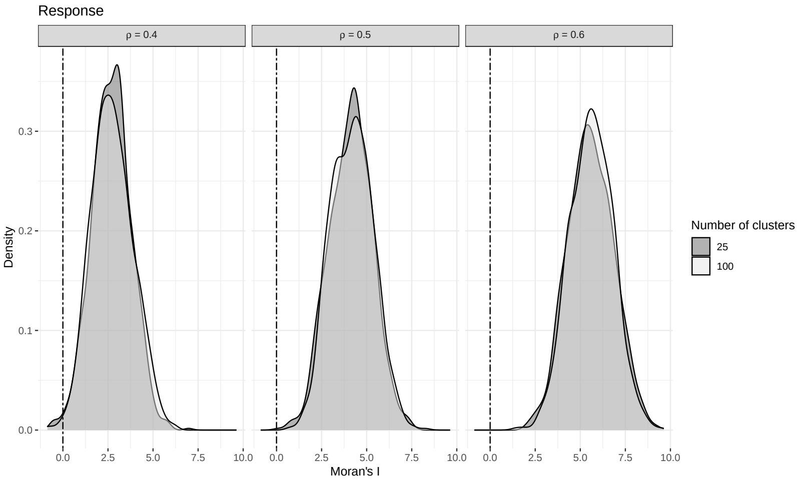

Figure A.17: Moran's I Response $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35$

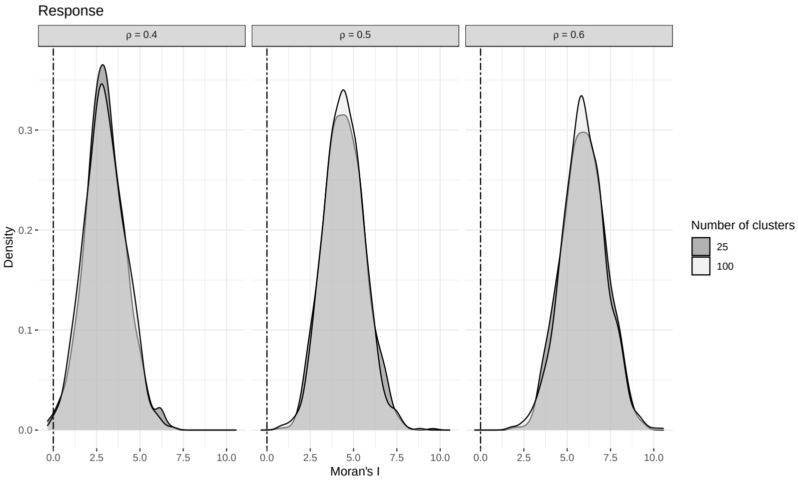

Figure A.18: Moran's I Response $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50$

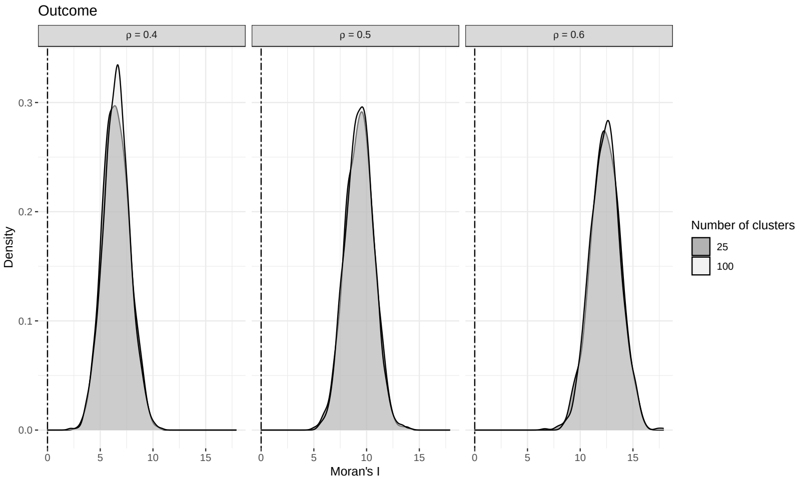

Figure A.19: Moran's I Outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20$

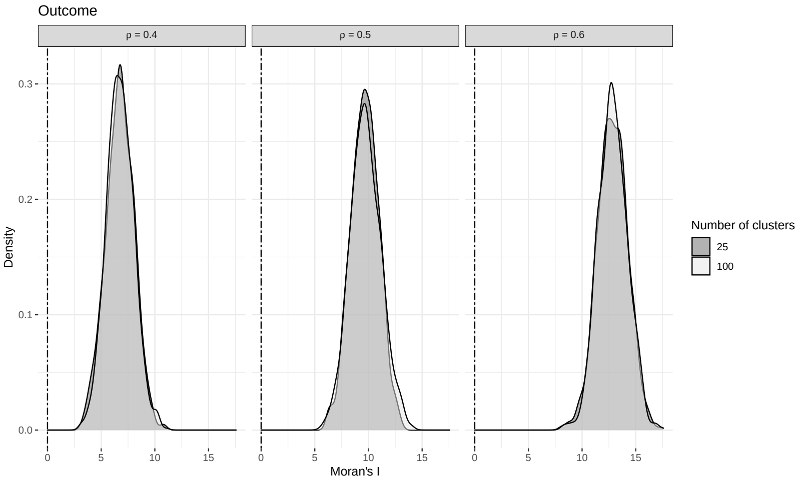

Figure A.20: Moran's I Outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35$

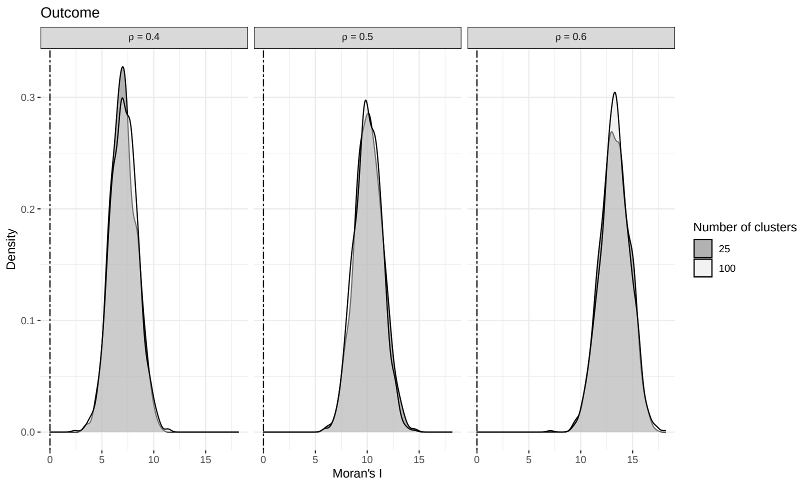

Figure A.21: Moran's I Outcome $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50$

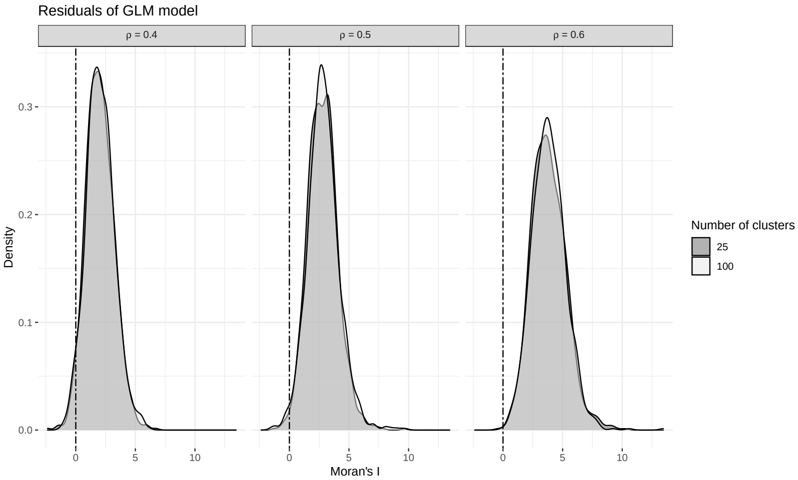

Figure A.22: Moran's I GLM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20$

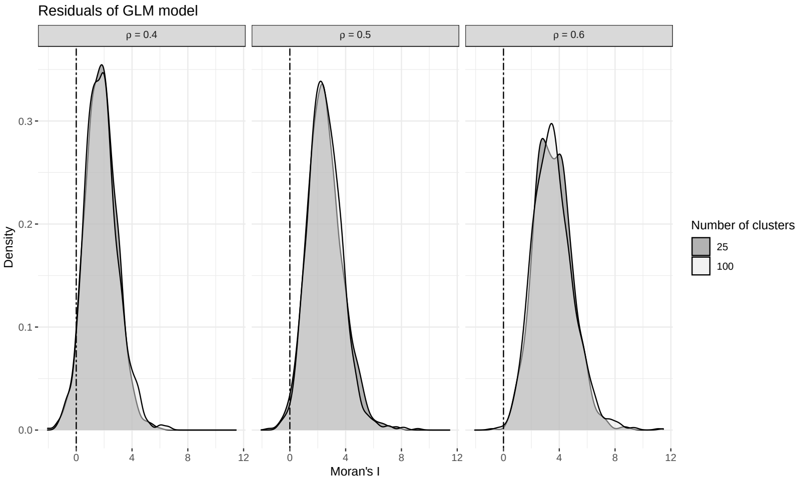

Figure A.23: Moran's I GLM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6, \ cov(uX1, oX1) = -0.35$

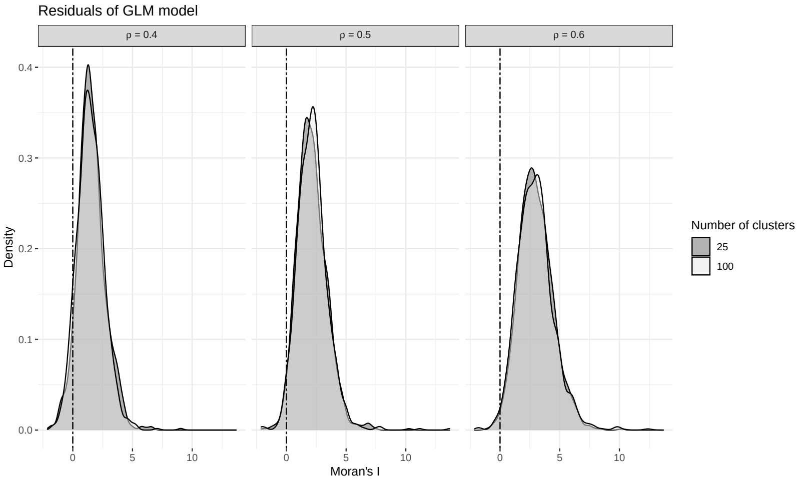

Figure A.24: Moran's I GLM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50$

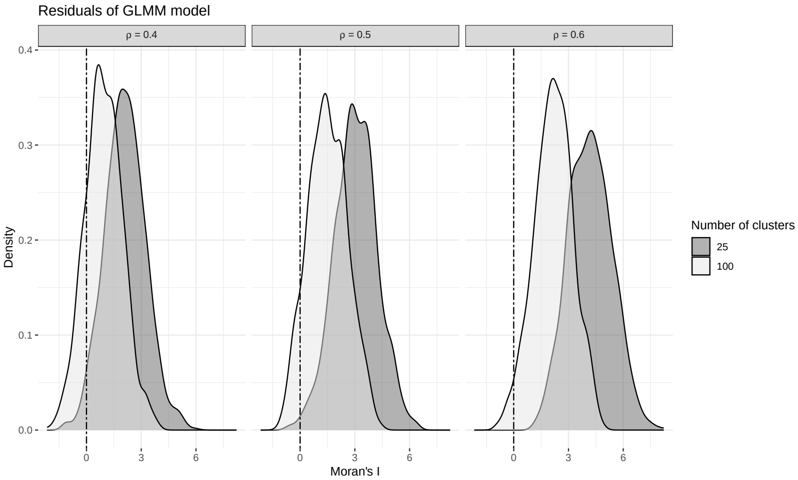

Figure A.25: Moran's I GLMM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20$

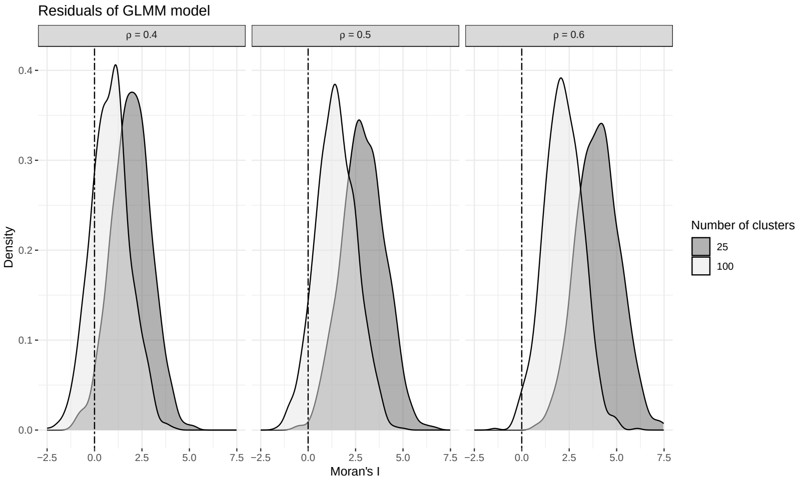

Figure A.26: Moran's I GLMM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35$

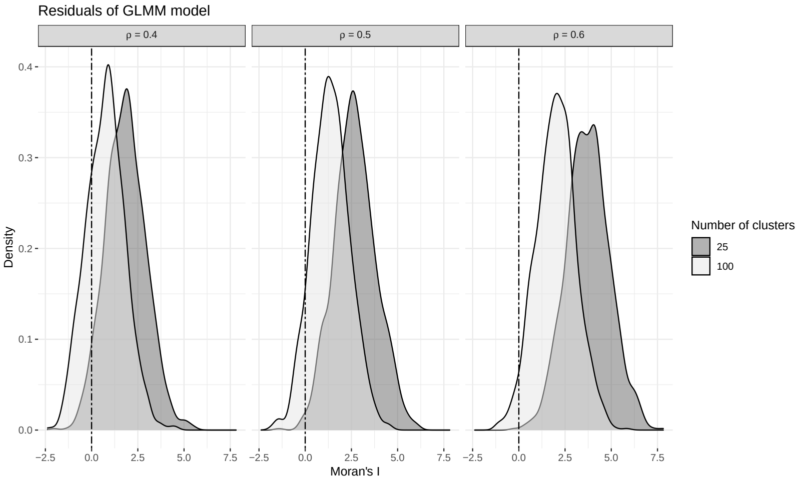

Figure A.27: Moran's I GLMM Residuals $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50$

Model performance

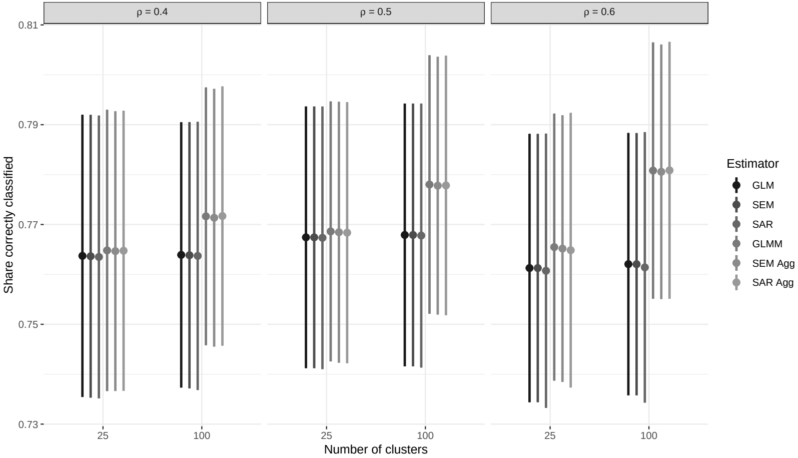

Figure A.28: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20$

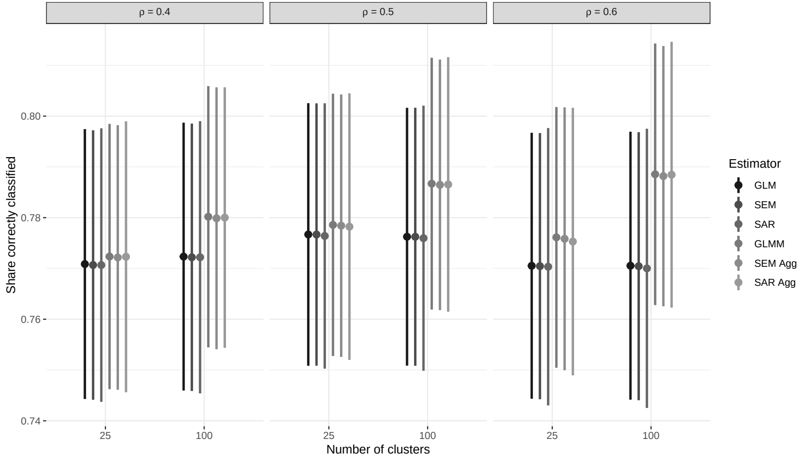

Figure A.29: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35$

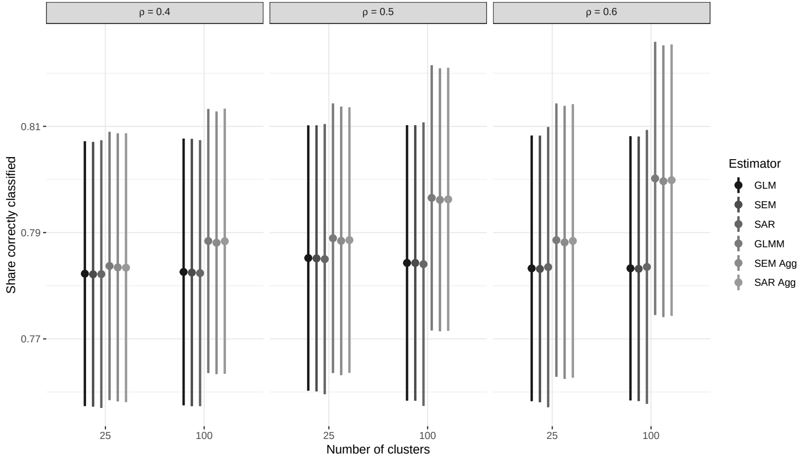

Figure A.30: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50$

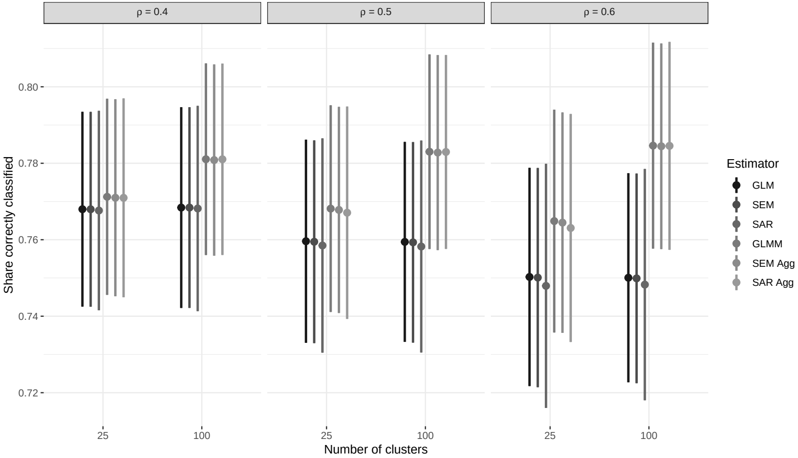

Figure A.31: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20$

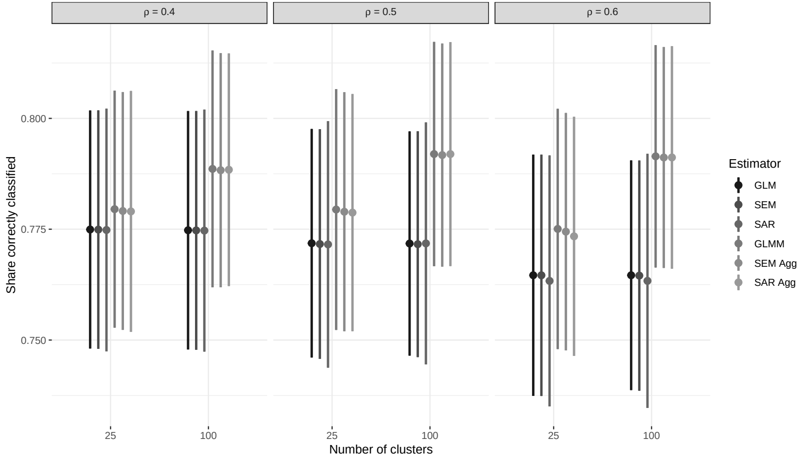

Figure A.32: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35$

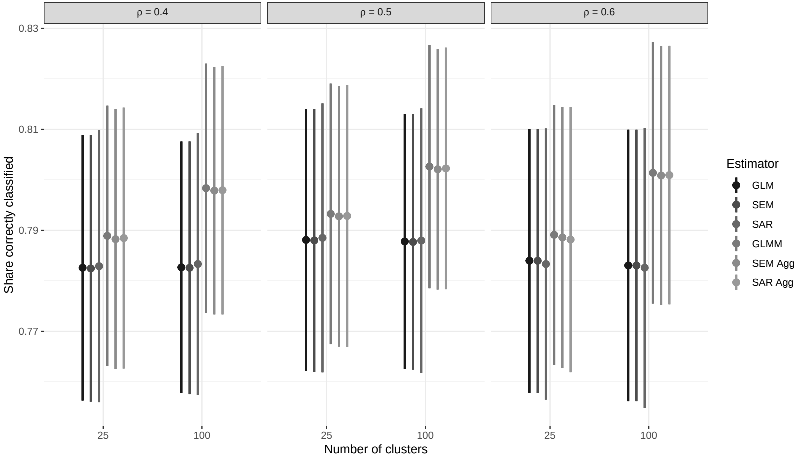

Figure A.33: Share correctly classified $\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50$

MSE weighted average (with weight trimming)

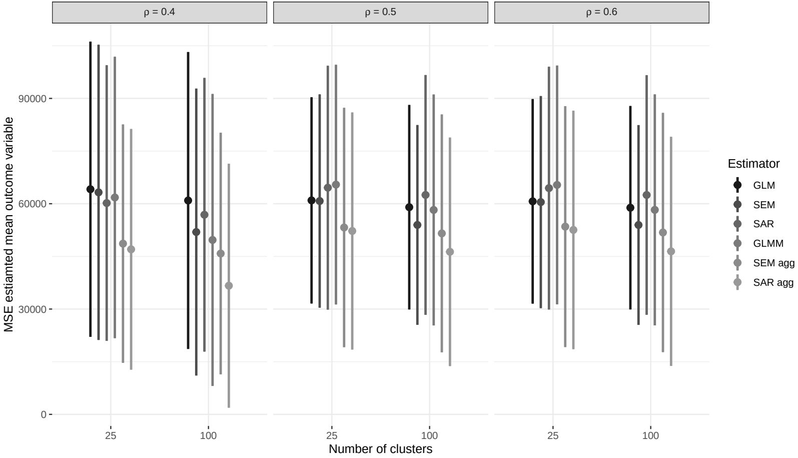

Figure A.34: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20, max.weight$: 99% quantile

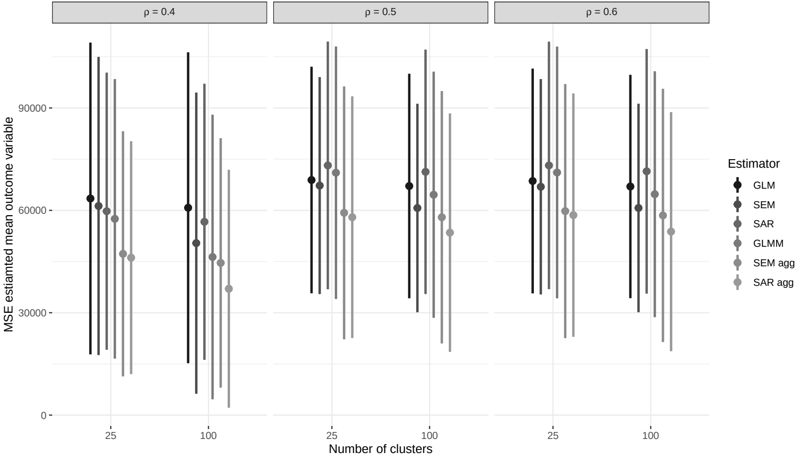

Figure A.35: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35, max.weight : 99\%$ quantile

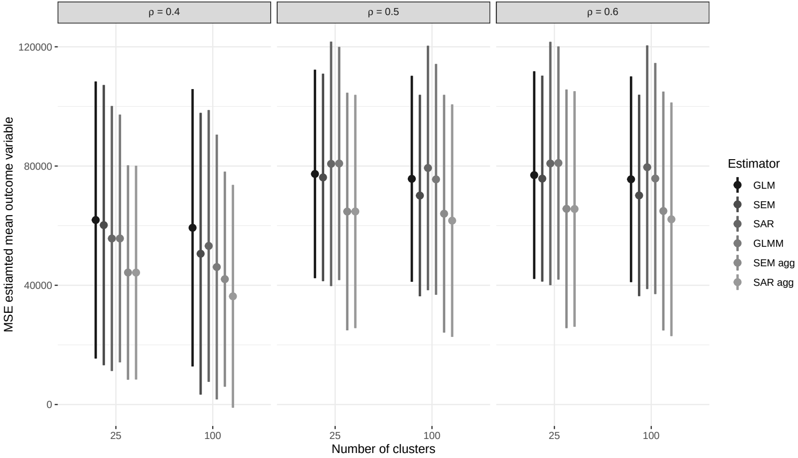

Figure A.36: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50, max.weight : 99\%$ quantile

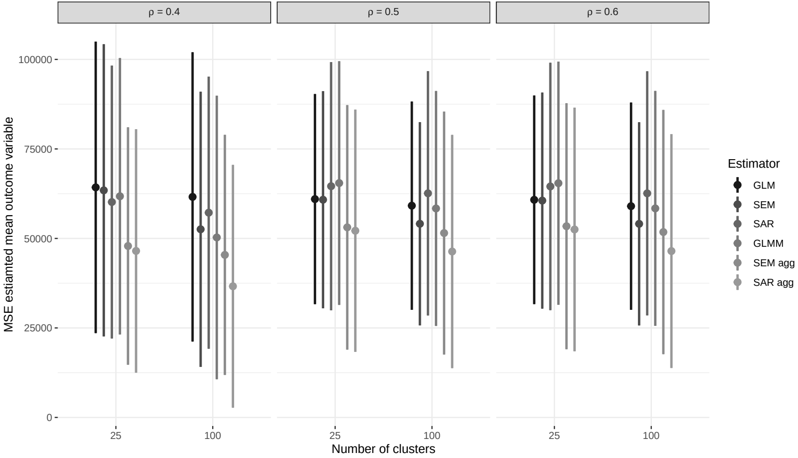

Figure A.37: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20, max.weight$: 95% quantile

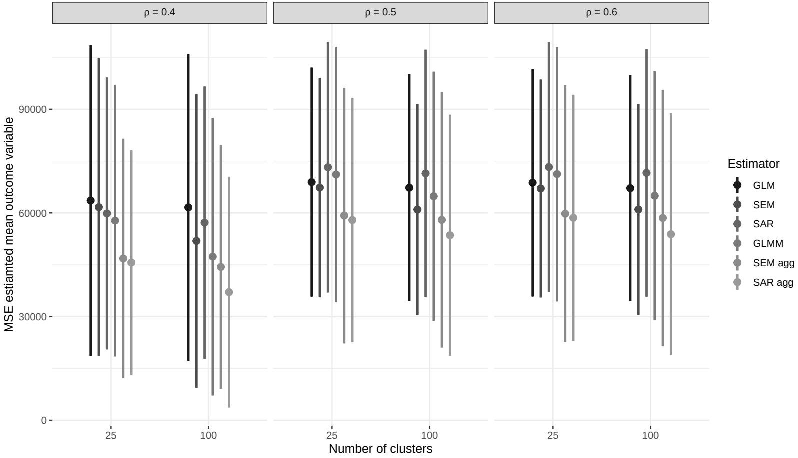

Figure A.38: Share correctly classified

$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35, max.weight$: 95% quantile

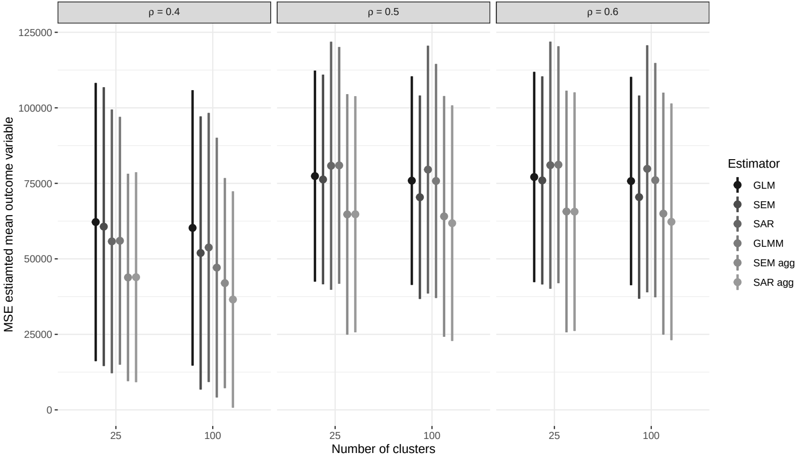

Figure A.39: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50, max.weight : 95\%$ quantile

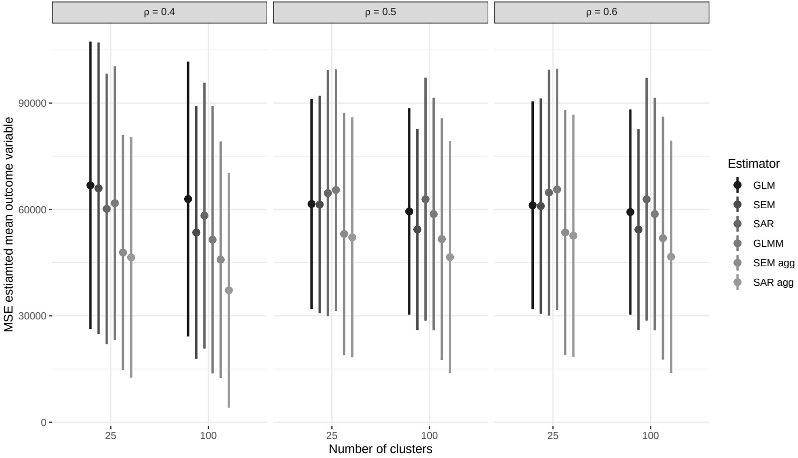

Figure A.40: Share correctly classified

$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = 0.20, max.weight : 90\%$ quantile

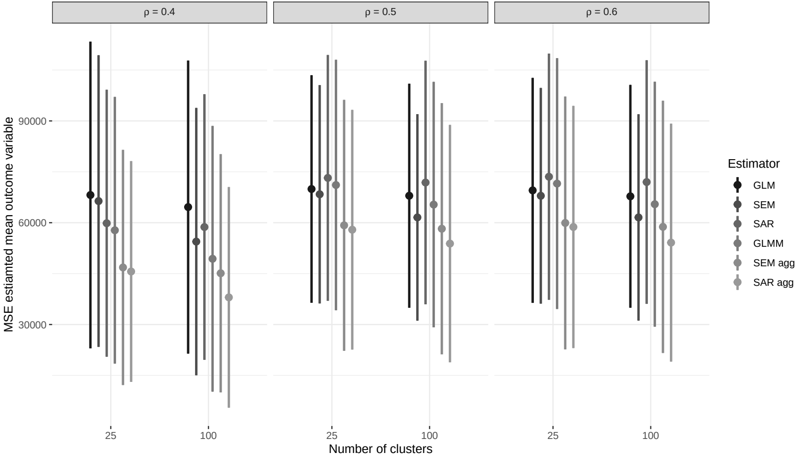

Figure A.41: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.35, max.weight : 90\%$ quantile

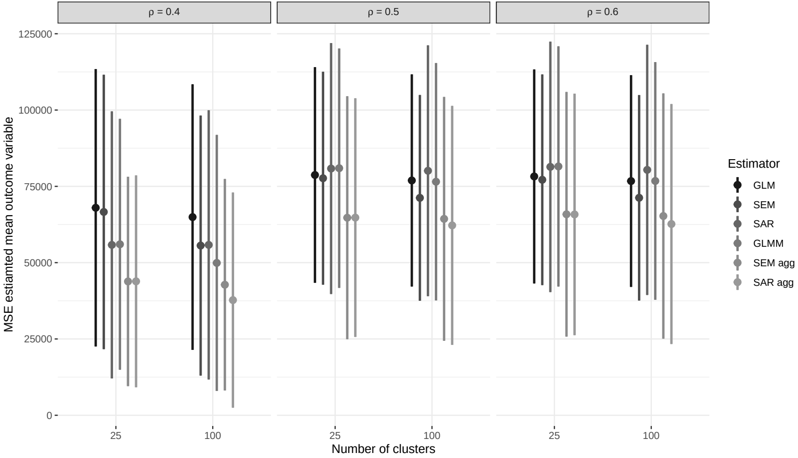

Figure A.42: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.5,\ cov(uX1, oX1) = -0.50, max.weight: 90\%$ quantile

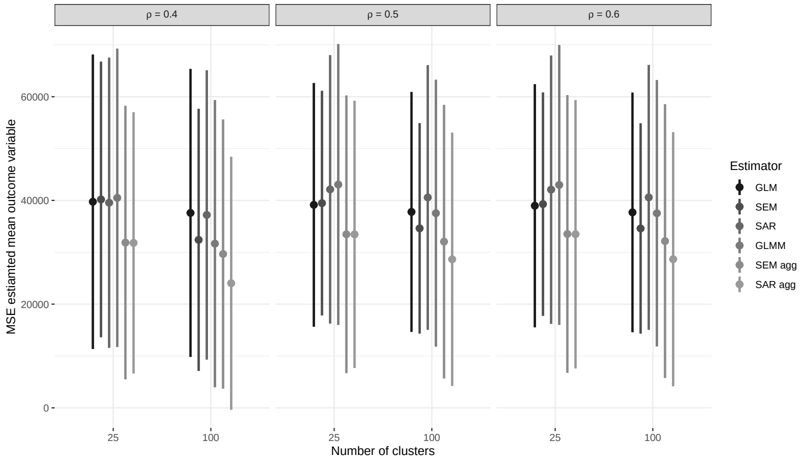

Figure A.43: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20, max.weight : 99\%$ quantile

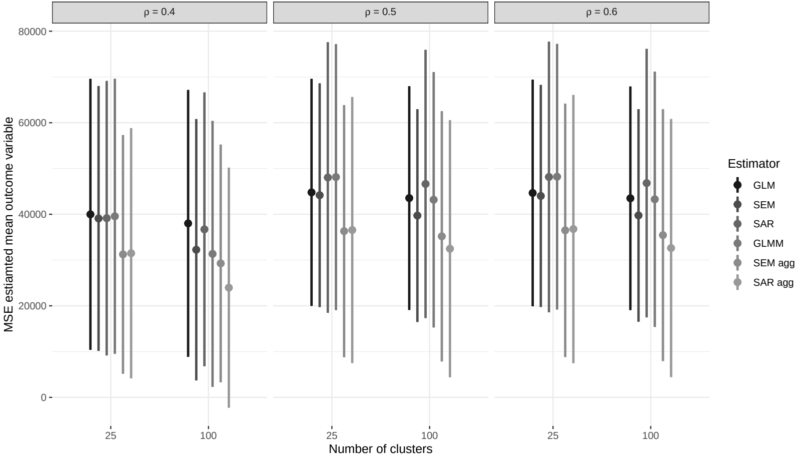

Figure A.44: Share correctly classified

$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35, max.weight : 99\%$ quantile

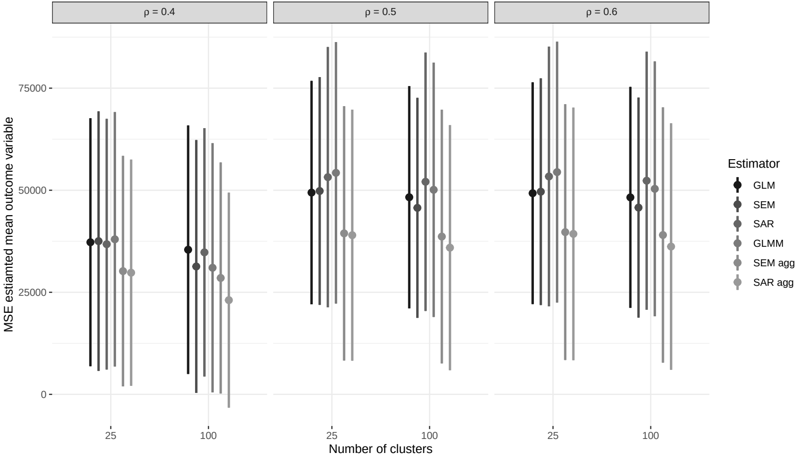

Figure A.45: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50, max.weight : 99\%$ quantile

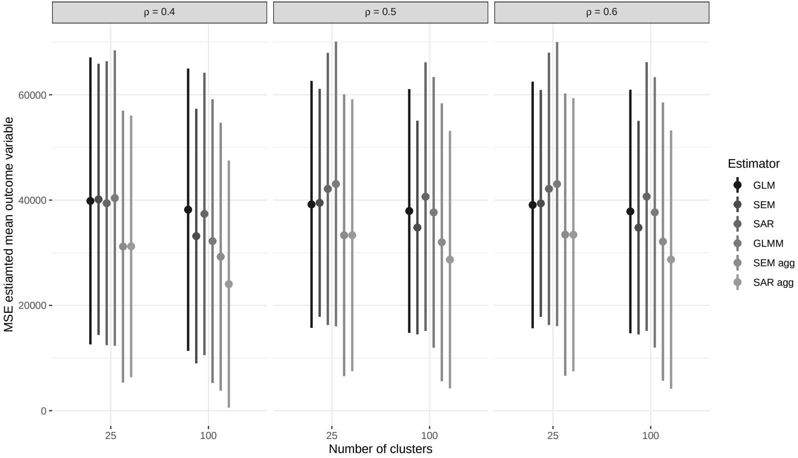

Figure A.46: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20, max.weight : 95\%$ quantile

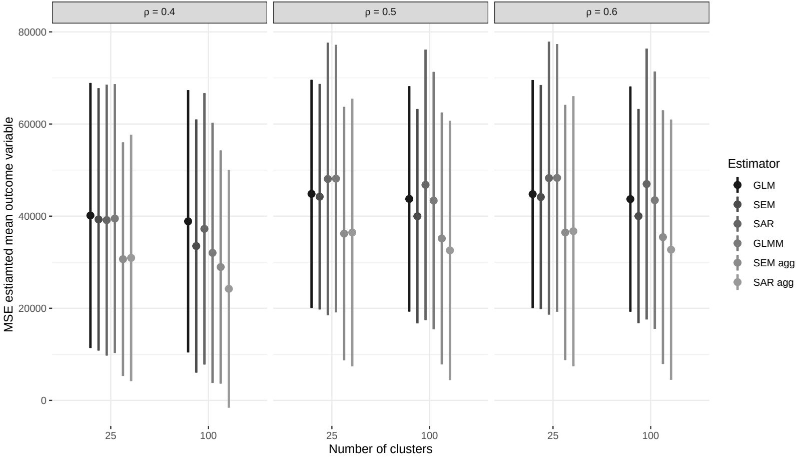

Figure A.47: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35, max.weight : 95\%$ quantile

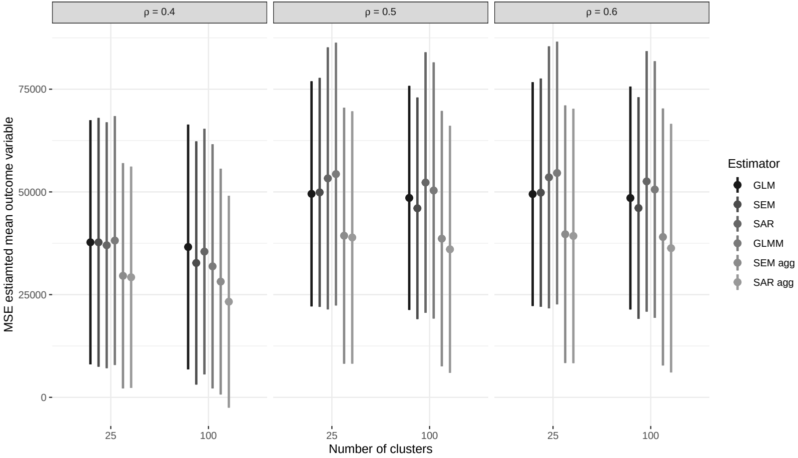

Figure A.48: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50, max.weight$: 95% quantile

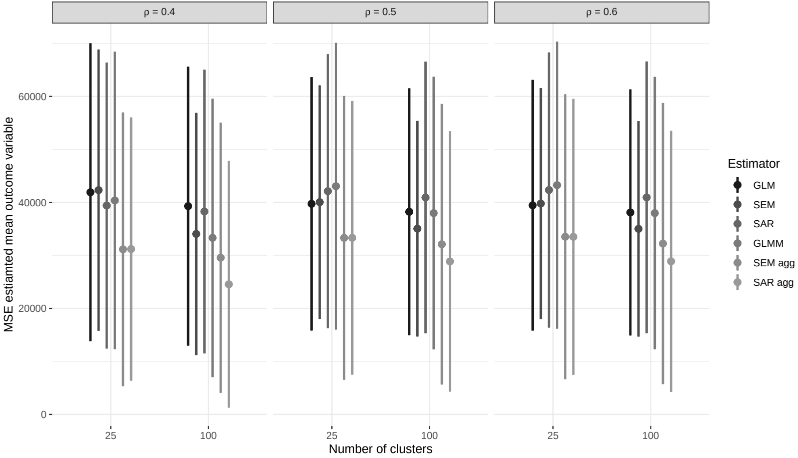

Figure A.49: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = 0.20, max.weight$: 90% quantile

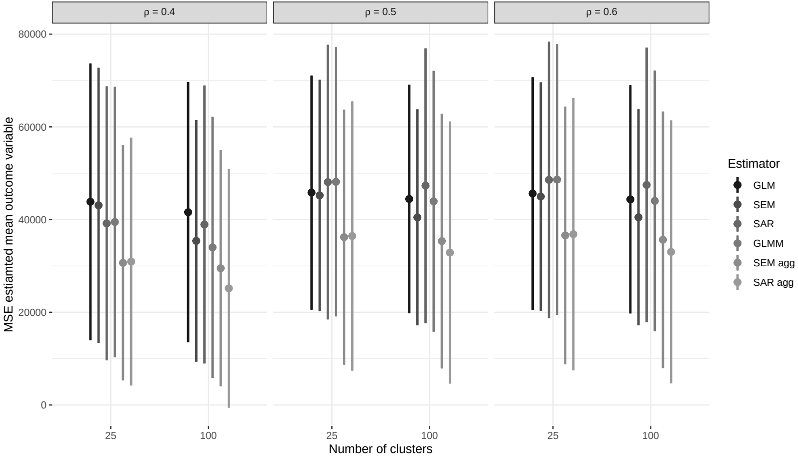

Figure A.50: Share correctly classified

$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.35, max.weight : 90\%$ quantile

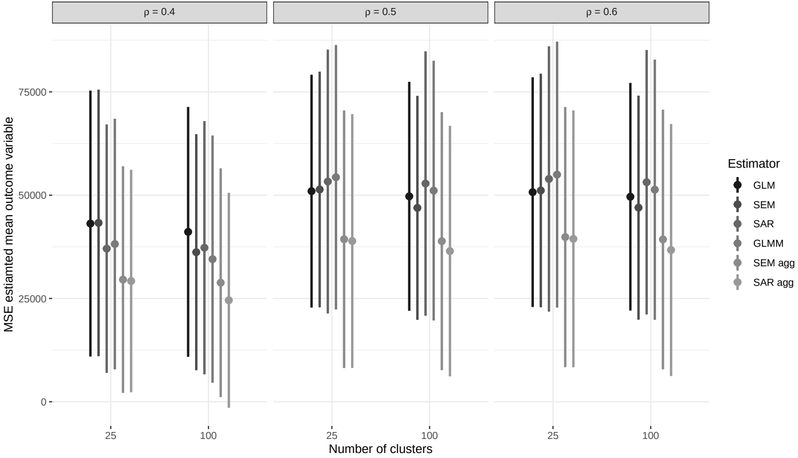

Figure A.51: Share correctly classified
$\mathbb{E}[\phi(\boldsymbol{X})] \approx 0.6,\ cov(uX1, oX1) = -0.50, max.weight : 90\%$ quantile