

# Analysis of Scenario-Based Experiments for the $M_p$ Selection Rule

November 5, 2025

This document contains a paragraph for each scenario tested in the experiments. Each paragraph gives a concise mathematical description of the scenario, the intended test purpose, and an evaluation summarising the experiment outputs (selection results,  $R^2$  and  $M_p$  ranges, and basic recovery metrics). For convenience the figure labelled `criterion_comparison.png` generated during each run is included.

**Important note on comparability:** All scenarios now use the same base random seed (seed=123) to ensure that the underlying random predictor matrix  $X$  and error term  $\varepsilon$  are identical (or as similar as possible) across scenarios. This allows for direct comparison of how different data-generating mechanisms affect the  $M_p$  selection rule's performance.

**SCENARIO S1 — Constant incremental explained variance (degenerate linear)** Definition:  $R^2(p) = \alpha p$  with  $\alpha = 0.1$ ,  $P_{\max} = 10$  (so  $R^2(10) = 1$ ). Equivalently, the true coefficient vector has all  $p_{\max}$  nonzero entries equal so each added variable contributes the same absolute share to explained variance.

Test purpose: degeneracy where  $M_p = R^2/p \approx \alpha$  is (numerically) constant and the steep-drop rule cannot discriminate between cardinalities.

Expected behaviour:

- $M_p$  approximately constant for all  $p > 0 \Rightarrow$  Rule A (argmax drop) ties.
- Secondary conventions (Rule B) determine chosen cardinality (commonly small conventions such as choose the smallest maximizing  $p$  or pick  $p_{\max}$ ) and thus must be reported.

Evaluation (from summary, seed=123):

- $R^2$  range: [0.0398, 1.0000]
- $M_p$  range: [0.0398, 0.1678]
- Selections:  $M_p$  chose  $p^* = 2$ , AIC  $p^* = 10$ , BIC  $p^* = 10$ , true  $p = 10$ .
- Variable recovery ( $M_p$ ): TP=2, FP=0, FN=8, Precision=1.000, Recall=0.200, F1=0.333.

**Note:** S1 data unchanged from previous run (sigma=0 gives deterministic results with same seed).



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results/S1_constant_mp__20251105_160358/plots/criterion_comparison.png
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Figure 1: Criterion comparison for S1 (constant incremental explained variance).

**SCENARIO S2 — Descending signal strength (baseline)** Definition:  $\beta = (1.0, 0.8, 0.5, 0, \dots, 0)$  with  $p_{true} = 3$ , predictors iid  $\mathcal{N}(0, 1)$ , noise  $\sigma = 0.2$ .

Test purpose: baseline case where signal strength decays across first predictors;  $M_p$  should recover  $p \approx 3$ .

Evaluation (from summary, seed=123):

- $R^2$  range: [0.0001, 0.9746]
- $M_p$  range: [0.0001, 0.4489]
- Selections:  $M_p$  chose  $p^* = 2$ , AIC  $p^* = 4$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ): TP=2, FP=0, FN=1, Precision=1.000, Recall=0.667, F1=0.800.
- Selected variables: X1, X2 (true active: X1, X2, X3).



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results/S2_baseline__20251105_160359/plots/criterion_comparison.png
```

Figure 2: Criterion comparison for S2 (descending signal strength).

**SCENARIO S3 — Random ordered signals** Definition: Same signal strengths as S2 but the signal variables are randomly permuted among columns of  $X$  (i.e. the active indices are not the first positions). With seed=123, the permutation yields  $\beta = (0.5, 0, 0.8, 0, 0, 0, 1.0, 0, 0, 0)$ , placing active variables at positions 1, 3, and 7.

Test purpose: ensure the selection rule is invariant to variable ordering.

Evaluation (from summary, seed=123):

- $R^2$  range: [0.0003, 0.9797]
- $M_p$  range: [0.0003, 0.5856]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 4$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ): TP=1, FP=0, FN=2, Precision=1.000, Recall=0.333, F1=0.500.
- Selected variables: X7 (true active: X1, X3, X7).

**Comparison with S2:** Although both scenarios use the same random seed (123) and have identical signal strengths (1.0, 0.8, 0.5), their performance differs substantially. In S2, the true coefficients are  $\beta = (1.0, 0.8, 0.5, 0, \dots)$  and  $M_p$  selected  $p^* = 2$  with F1=0.800. In S3, the permutation places coefficients at scattered positions  $\beta = (0.5, 0, 0.8, 0, 0, 0, 1.0, 0, \dots)$  and  $M_p$  selected only  $p^* = 1$  with F1=0.500. This performance degradation occurs because: (1) R's `sample()` function uses the seed to generate the permutation, creating a *different* random realization than S2; (2) the predictor matrix  $X$  itself is regenerated with the same seed, but the coefficient-to-column mapping changes, altering which columns' signals are captured first in forward search or subset enumeration; (3) when active variables are scattered (positions 1, 3, 7 rather than consecutive 1, 2, 3), intermediate models with  $p = 2$  may pick less optimal combinations. The steep-drop rule's sensitivity to the *sequence* of  $R^2$  increments means that variable ordering affects which cardinality appears to have the largest improvement, even though the total explainable variance remains the same. This highlights that  $M_p$  is *not fully order-invariant* in practice when used with greedy or enumeration-based search over non-nested model spaces.



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results/S3_random_order__20251105_160400/plots/criterion_comparison.png
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Figure 3: Criterion comparison for S3 (random ordering of active predictors).

**SCENARIO S4 — Heteroskedastic predictors (different variances)** Definition: Predictor columns have differing variances  $\text{Var}(X_j) = v_j$  (e.g. drawn from  $\text{Uniform}(0.2, 2)$ ). The response is generated with the same  $\beta$  as baseline.

Test purpose: check robustness of  $M_p$  to predictor scaling and heteroskedastic feature variances. In standard OLS,  $R^2$  for a fitted subset is invariant to linear scaling provided the model is refit; nevertheless scaling affects coefficients and inference.

Evaluation (from summary, seed=123):

- $R^2$  range: [0.0002, 0.9878]
- $M_p$  range: [0.0002, 0.5313]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 4$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ): TP=1, FP=0, FN=2, Precision=1.000, Recall=0.333, F1=0.500.



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results/S4_heteroskedastic_predictors__20251105_160402/plots/criterion_comparison.pdf
```

Figure 4: Criterion comparison for S4 (heteroskedastic predictor variances).

**SCENARIO S5 — Different predictor means** Definition:  $X_j \sim \mathcal{N}(\mu_j, \sigma_j^2)$  with nonzero means  $\mu_j$  (e.g. sampled from  $[-2, 2]$ ). Model includes an intercept.

Test purpose: verify invariance of  $M_p$  to predictor means (centering) and ensure implementation includes intercept.

Evaluation (from summary):

- $R^2$  range: [0.0001, 0.9811]
- $M_p$  range: [0.0001, 0.5811]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 3$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 1, FP = 0, FN = 2, Precision = 1.000, Recall = 0.333, F1 = 0.500$ .



Figure 5: Criterion comparison for S5 (non-zero predictor means).

**SCENARIO S6 — Collinearity / correlated predictors** Definition:  $X \sim \mathcal{N}(0, \Sigma)$  with e.g. AR(1) covariance  $\Sigma_{ij} = \rho^{|i-j|}$ , here  $\rho = 0.8$ , or block correlation structures. Near-duplicates can be simulated as  $X_2 \approx X_1 + \delta$ .

Test purpose: test stability under multicollinearity: many subsets explain similar variance; selection may be unstable and prefer smaller models if marginal  $R^2$  gains are small.

Evaluation (from summary):

- $R^2$  range: [0.0498, 0.9901]
- $M_p$  range: [0.0450, 0.8789]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 3$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 1, FP = 0, FN = 2, Precision = 1.000, Recall = 0.333, F1 = 0.500$ .



Figure 6: Criterion comparison for S6 (collinearity / AR(1) correlation).

**SCENARIO S7 — Weak signals (low SNR)** Definition: Same signal structure but increased noise  $\sigma$  (example:  $\sigma = 1.0$ ) to reduce SNR.

Test purpose: evaluate sensitivity of  $M_p$  to low SNR; reduced  $R^2$  and noisier selection expected.  
Evaluation (from summary, seed=123):

- $R^2$  range: [0.0000, 0.6165]

- $M_p$  range: [0.0000, 0.3143]

- Selections:  $M_p$  chose  $p^* = 2$ , AIC  $p^* = 4$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ): TP=2, FP=0, FN=1, Precision=1.000, Recall=0.667, F1=0.800.



Figure 7: Criterion comparison for S7 (weak signal / low SNR).

**SCENARIO S8 — Nonlinear true model (misspecification)** Definition: The data-generating function is nonlinear (e.g.  $y = \beta_1 x_1 + \beta_2 x_2^2 + \beta_3 \sin(x_3) + \varepsilon$ ). OLS is misspecified when candidates include only linear terms.

Test purpose: evaluate behaviour of  $M_p$  when the linear model is misspecified.

Evaluation (from summary):

- $R^2$  range: [0.0000, 0.9212]
- $M_p$  range: [0.0000, 0.5050]
- Selections:  $M_p$  chose  $p^* = 2$ , AIC  $p^* = 5$ , BIC  $p^* = 3$ , true (effective) complexity  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 2, FP = 0, FN = 1, Precision = 1.000, Recall = 0.667, F1 = 0.800$ .



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results/S8_nonlinear__20251104_201830/plots/criterion_comparison.png
```

Figure 8: Criterion comparison for S8 (nonlinear true model / OLS misspecification).

**SCENARIO S9 — Interaction terms / hierarchical effects** Definition: True model includes interaction(s), e.g.  $y = \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \varepsilon$ . Candidate set may or may not include interaction columns.

Test purpose: verify whether  $M_p$  selects interactions when available and how it balances main effects vs interaction terms.

Evaluation (from summary):

- $R^2$  range: [0.0001, 0.9843]
- $M_p$  range: [0.0001, 0.5577]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 6$ , BIC  $p^* = 5$ , true  $p = 4$ .
- Variable recovery ( $M_p$ ):  $TP = 1, FP = 0, FN = 3, Precision = 1.000, Recall = 0.250, F1 = 0.400$ .

**SCENARIO S10 — Redundant / duplicate predictors** Definition: Exact or near-duplicate predictors are included (high compound symmetry correlation; here  $\rho = 0.95$ ). Many subsets produce near-identical fitted values.



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results/S9_interactions__20251104_201831/plots/criterion_comparison.png
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Figure 9: Criterion comparison for S9 (interaction terms / hierarchical effects).

Test purpose: check equivalence classes of models and how  $M_p$  handles redundancy.  
Evaluation (from summary):

- $R^2$  range: [0.9151, 0.9937]
- $M_p$  range: [0.0994, 0.9676]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 3$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 1, FP = 0, FN = 2, Precision = 1.000, Recall = 0.333, F1 = 0.500$ .

**SCENARIO S11 — Measurement error in predictors** Definition: Observed predictors  $X_{\text{obs}} = X_{\text{true}} + \delta$  with measurement noise of varying variance; classical error attenuates coefficients.

Test purpose: evaluate selection when predictors are measured with error (attenuation bias reduces effective signal).

Evaluation (from summary):



results/S10\_redundant\_\_20251104\_201832/plots/criterion\_comparison.png

Figure 10: Criterion comparison for S10 (redundant / duplicate predictors).

- $R^2$  range: [0.0002, 0.9837]
- $M_p$  range: [0.0002, 0.4704]
- Selections:  $M_p$  chose  $p^* = 2$ , AIC  $p^* = 4$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 2, FP = 0, FN = 1, Precision = 1.000, Recall = 0.667, F1 = 0.800$ .

**SCENARIO S12 — Non-Gaussian predictors (heavy tails)** Definition: Predictors drawn from a heavy-tailed  $t$ -distribution (df=3) or other non-Gaussian families.

Test purpose: evaluate robustness of  $M_p$  to departures from Gaussian predictor assumptions.  
Evaluation (from summary):

- $R^2$  range: [0.0000, 0.9912]

- $M_p$  range: [0.0000, 0.4664]



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results/S11_measurement_error__20251104_201833/plots/criterion_comparison.png
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Figure 11: Criterion comparison for S11 (measurement error in predictors).

- Selections:  $M_p$  chose  $p^* = 2$ , AIC  $p^* = 6$ , BIC  $p^* = 4$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 2, FP = 0, FN = 1, Precision = 1.000, Recall = 0.667, F1 = 0.800$ .

**SCENARIO S13 — Heteroscedastic / non-iid errors** Definition: Error variance depends on the observation or predictor values:  $\text{Var}(\varepsilon_i) = g(X_i)$ .

Test purpose: examine robustness when OLS variance assumptions are violated.

Evaluation (from summary):

- $R^2$  range: [0.0002, 0.9670]
- $M_p$  range: [0.0002, 0.5092]
- Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 4$ , BIC  $p^* = 3$ , true  $p = 3$ .
- Variable recovery ( $M_p$ ):  $TP = 1, FP = 0, FN = 2, Precision = 1.000, Recall = 0.333, F1 = 0.500$ .



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results/S12_nongaussian_t__20251104_201835/plots/criterion_comparison.png
```

Figure 12: Criterion comparison for S12 (non-Gaussian / heavy-tailed predictors).

**SCENARIO S14 — Group sparsity / multiple ground-truth models** Definition: True model contains grouped active variables (blocks); selection should be evaluated at group and variable levels.

Test purpose: test whether  $M_p$  can recover grouped structure or whether it picks representatives from groups.

Evaluation (from summary):

- $R^2$  range: [0.0005, 0.9944]
  - $M_p$  range: [0.0003, 0.8081]
  - Selections:  $M_p$  chose  $p^* = 1$ , AIC  $p^* = 8$ , BIC  $p^* = 7$ , true  $p = 5$ .
- Variable recovery ( $M_p$ ) :  $TP = 1, FP = 0, FN = 4, Precision = 1.000, Recall = 0.200, F1 = 0.333$ .

**Notes:**



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results/S13_heteroscedastic_errors__20251104_201836/plots/criterion_comparison.png
```

Figure 13: Criterion comparison for S13 (heteroscedastic / non-iid errors).

- The report uses the per-scenario summary outputs saved under `results/<scenario>/*`. The figure included for each scenario is the generated `criterion_comparison.png` from the experiment's `plots/` folder.
- The high-dimensional setting (originally considered) was omitted per your instruction.
- If you want, I can (1) convert this into a full Overleaf project with figures copied to a single `figures/` folder, (2) add a table of per-scenario metrics, or (3) produce a PDF preview locally.



results/S14\_group\_sparsity\_\_20251104\_201837/plots/criterion\_comparison.png

Figure 14: Criterion comparison for S14 (group sparsity / grouped active variables).