
LINEAR INTERACTION OF TREATMENT WITH BASELINE RISK WAS SUFFICIENT FOR PREDICTING INDIVIDUALIZED BENEFIT

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Abstract

data using diverse assumptions for a baseline prognostic index of risk (PI) and the shape of its interaction with treatment (none, linear or quadratic). In constant relative treatment effect; models including an interaction of treatment with the PI; stratification in quarters of the PI; nonlinear transformations of the PI (restricted cubic splines with 3, 4 and 5 knots); an adaptive approach using Akaike's Information Criterion. We evaluated predictive performance using root mean squared error and measures of discrimination and calibration for benefit. Starting from a base case scenario (sample size 4,250, treatment odds ratio 0.8, AUC of the PI 0.75), we varied the sample size, the treatment effect PI by treatment interaction performed better under most simulation settings. Flexible models required larger sample sizes and higher AUC of the PI to outperform the linear interaction model. The adaptive approach tended to select simpler models with smaller sample sizes and/or worse prediction performance. the PI with treatment is the optimal risk-based approach to predicting absolute treatment benefit. **Objective:** To compare different risk-based methods predicting individualized treatment effects in RCT simulations.

Study Design and Setting: We simulated each sample we predicted absolute benefit using: models with the PI and a strength, and the PI's discriminative ability. **Results:** Models including a **Conclusion:** Under most circumstances, a model with a linear interaction of

Keywords treatment effect heterogeneity · absolute benefit · prediction models

1 1 Introduction

2 Predictive approaches for assessing heterogeneity of treatment effects (HTE) aim at the development of models
3 predicting either individualized effects or which of two (or more) treatments is better for an individual [1]. In prior
4 work, we divided such methods in three broader categories based on the reference class used for defining patient
5 similarity when making individualized predictions or recommendations [2]. Risk-modeling approaches use prediction
6 of baseline risk as the reference; treatment effect modeling approaches also model treatment-covariate interactions,
7 in addition to risk factors; optimal treatment regime approaches focus on developing treatment assignment rules
8 and therefore rely heavily on modeling treatment effect modifiers.

9 Risk-modeling approaches to predictive HTE analyses provide a viable option in the absence of well-established
10 treatment effect modifiers [3,4]. In simulations, modeling of effect modifiers, i.e. treatment-covariate interactions,
11 often led to miscalibrated predictions of benefit, while risk-based methods proved quite robust [5]. Most often,
12 risk-modeling approaches are carried out in two steps: first a risk prediction model is developed externally or
13 internally on the entire RCT population, “blinded” to treatment; then the RCT population is stratified using this
14 prediction model to evaluate risk-based treatment effect variation [6]. However, even though estimates at the risk
15 subgroup level may be accurate, these estimates do not apply to individual patients, especially for patients with
16 predicted risk at the boundaries of the risk intervals. Hence, the risk-stratified approach is useful for exploring and
17 presenting HTE, but is not useful for supporting treatment decisions for individual patients.

18 To individualize treatment effects, the recent PATH statement suggested various risk-based models including a
19 prognostic index of baseline risk (PI) and treatment assignment [3,4]. We aimed to summarize and compare
20 different risk-based models for predicting individualized treatment effects. We simulated RCT settings to compare
21 the performance of these models under different assumptions of the relationship between baseline risk and treatment.
22 We illustrated the different models by a case study of predicting individualized effects of tissue plasminogen
23 activator (tPA) versus streptokinase treatment in patients with an acute myocardial infarction (MI).

24 2 Methods

25 2.1 Simulation scenarios

26 For each patient we generated 8 baseline covariates here $x_1, \dots, x_4 \sim N(0, 1)$ and $x_5, \dots, x_8 \sim B(1, 0.2)$.
27 Treatment was allocated using a 50:50 split. Outcomes for patients in the control arm were generated from a logistic
28 regression model including all baseline covariates. In the base scenarios coefficient values were such, that the AUC of
29 the logistic regression model was 0.75 and the event rate in the control arm was 20%. Binary outcomes in the control
30 arm were generated from Bernoulli variables with true probabilities $P(y = 1|X, t_x = 0) = \text{expit}(PI) = \frac{e^{PI}}{1+e^{PI}}$.
31 Outcomes in the treatment arm were generated using 3 base scenarios: absent treatment effect ($OR = 1$), moderate
32 treatment effect ($OR = 0.8$) and high treatment effect ($OR = 0.5$). We started with simulating outcomes based

1 on true constant relative treatment effects for the 3 base scenarios. We then simulated linear, quadratic and
2 non-monotonic deviations from constant treatment effects using:

$$lp_1 = \gamma_2(PI - c)^2 + \gamma_1(PI - c) + \gamma_0,$$

3 where lp_1 is the true linear predictor in the treatment arm, so that $P(y = 1|X, t_x = 1) = \text{expit}(lp_1)$. Finally, we
4 simulated scenarios where a constant absolute harm is applied across all treated patients. In this case we have
5 $P(y = 1|X, t_x = 1) = \text{expit}(lp_1) + \text{harm}$.

6 The sample size for the base scenarios was set to 4,250 (80% power for the detection of a marginal OR of 0.8).

7 We evaluated the effect of smaller or larger sample sizes of 1,063 and 17,000, respectively. We also evaluated the
8 effect of worse or better discriminative ability for risk, adjusting the baseline covariate coefficients, such that the
9 AUC of the regression model in the control arm was 0.65 and 0.85 respectively.

10 Combining all these settings resulted in a simulation study of 486 scenarios (exact settings in the supplementary
11 material).

12 2.2 Individualized risk-based benefit predictions

13 All methods assume that a risk prediction model is available to assign risk predictions to individual patients. For
14 the simulations we developed a prediction model internally, using logistic regression including main effects for all
15 baseline covariates and treatment assignment. Risk predictions for individual patients were based on treatment
16 assignment to the control arm, that is setting treatment assignment to 0.

17 A *stratified HTE method* has been suggested as an alternative to traditional subgroup analyses. Patients are
18 stratified into equally-sized risk strata—in this case based on risk quartiles. Absolute treatment effects within risk
19 strata are estimated by the difference in event rate between patients in the control arm and patients in the treated
20 arm. We considered this approach as a reference, expecting it to perform worse than the other candidates, as its
21 objective is not to individualize benefit prediction.

22 Second, we considered a model which assumes *constant relative treatment effect* (constant OR). Hence, absolute
23 benefit is predicted from $\hat{\tau}(\mathbf{x}) = \text{expit}(PI + \log(\text{OR}))$.

24 Third, we considered a logistic regression model including treatment, the prognostic index, and their linear
25 interaction. Absolute benefit is then estimated from $\hat{\tau}(\mathbf{x}) = \text{expit}(\beta_0 + \beta_{PI}PI) - \text{expit}(\beta_0 + \beta_{t_x} + (\beta_{PI} + \beta_*)PI)$.
26 We will refer to this method as the *linear interaction* approach.

27 Fourth, we used *restricted cubic splines* (RCS) to relax the linearity assumption on the effect of the linear predictor
28 [7]. We considered splines with 3, 4 and 5 knots to compare models with different levels of flexibility.

1 Finally, we considered an adaptive approach using Akaike's Information Criterion (AIC) for model selection. The
2 candidate models were: a constant treatment effect model, a model with a linear interaction with treatment and
3 RCS models with 3, 4 and 5 knots.

4 **2.3 Evaluation metrics**

5 We evaluated the predictive accuracy of the considered methods by the root mean squared error (RMSE):

$$\text{RMSE} = \frac{1}{n} \sum_{i=1}^n (\tau(\mathbf{x}_i) - \hat{\tau}(\mathbf{x}_i))^2$$

6 We compared the discriminative ability of the methods under study using c-for-benefit [8]. The c-for-benefit
7 represents the probability that from two randomly chosen matched patient pairs with unequal observed benefit,
8 the pair with greater observed benefit also has a higher predicted benefit. To be able to calculate observed benefit,
9 patients in each treatment arm are ranked based on their predicted benefit and then matched 1:1 across treatment
10 arms. *Observed* treatment benefit is defined as the difference of observed outcomes between the untreated and
11 the treated patient of each matched patient pair. *Predicted* benefit is defined as the average of predicted benefit
12 within each matched patient pair.

13 We evaluated calibration in a similar manner, using the integrated calibration index (ICI) for benefit [9]. The
14 observed benefits are regressed on the predicted benefits using a locally weighted scatterplot smoother (loess).
15 The ICI-for-benefit is the average absolute difference between predicted and smooth observed benefit. Values
16 closer to 0 represent better calibration.

17 **3 Results**

18 **3.1 Simulations**

19 The model including a constant relative treatment effect had the lowest median RMSE in scenarios with a true
20 constant relative treatment effect ($\text{OR} = 0.8$, $N = 4,250$ and $\text{AUC} = 0.75$) or with moderate relative deviations
21 (Figure 1; Panel A). However, when we considered strong linear and quadratic deviations from a constant relative
22 treatment effect the linear interaction model performed best (Figure 1; Panels B and C). Only in the case of strong
23 quadratic deviations models including RCS (3 knots) performed equally well to the linear interaction method.
24 Increasing the number of knots in RCS resulted in higher RMSE across all scenarios. The adaptive approach
25 selected a linear interaction model 35% of the time in the case of true strong linear deviations, while the majority
26 of the time (56%) it selected a simpler constant treatment effect model (Supplementary Table S7). Similarly, in
27 the case of true strong quadratic deviations, the adaptive approach selected the RCS (3 knots) model 29% of the
28 time, while the simpler linear interaction model was selected 68% of the time.

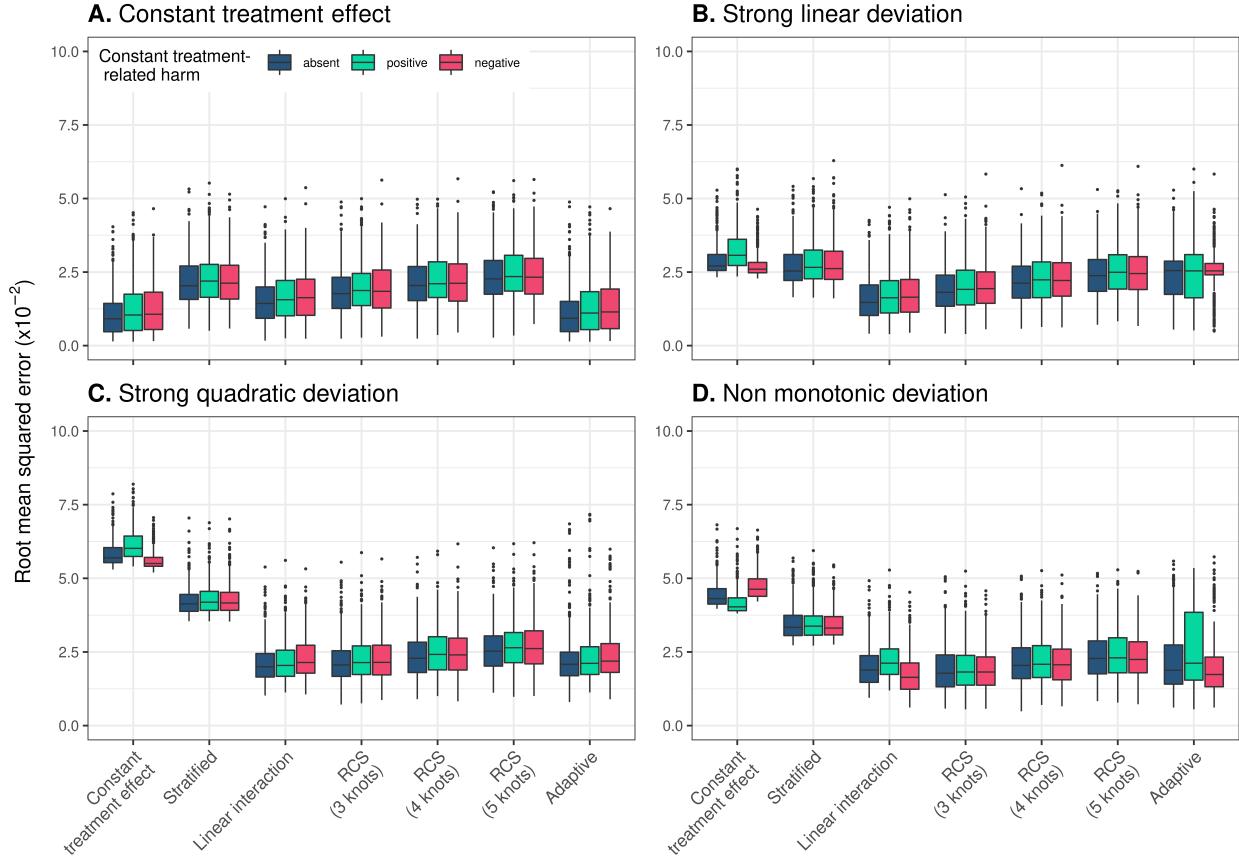


Figure 1: RMSE of the considered methods across 500 replications calculated in a simulated superpopulation of size 500,000. The scenario with true constant relative treatment effect had a true prediction AUC of 0.75 and sample size of 4250. Results are presented under moderate linear, strong linear, and strong quadratic deviations from constant relative treatment effects.

- 1 When we increased the sample size ($N = 17,000$), the model including a constant relative treatment effect had
- 2 the lowest RMSE under the assumption of true constant relative treatment effects (Figure 2; Panel A). However,
- 3 when introducing moderate and strong linear deviations the linear interaction model outperformed the constant
- 4 treatment effect model (Figure 2; Panels B and C). Furthermore, the linear interaction model was outperformed by
- 5 the more flexible RCS models (3 knots) in the case of strong quadratic deviations. Again, the increased flexibility
- 6 of RCS smoothing with higher number of knots resulted in overfitting and worse predictive accuracy (Figure 2;
- 7 Panel D).

- 8 When we increased the AUC of the true prediction model to 0.85, models including RCS smoothing had the lowest
- 9 RMSE in the presence of strong quadratic deviations from the base case of true constant relative treatment effects
- 10 (Figure 3; Panel D). However, with milder deviations, the linear interaction model had the lowest RMSE with the
- 11 RCS smoothing methods (3 knots) being a close second (Figure 3; Panels B and C). Increasing the number of
- 12 knots of RCS smoothing resulted in increased RMSE, which was less pronounced in the case of strong quadratic
- 13 deviations. With increasing prediction AUC we saw an increased tendency of the adaptive approach to select more

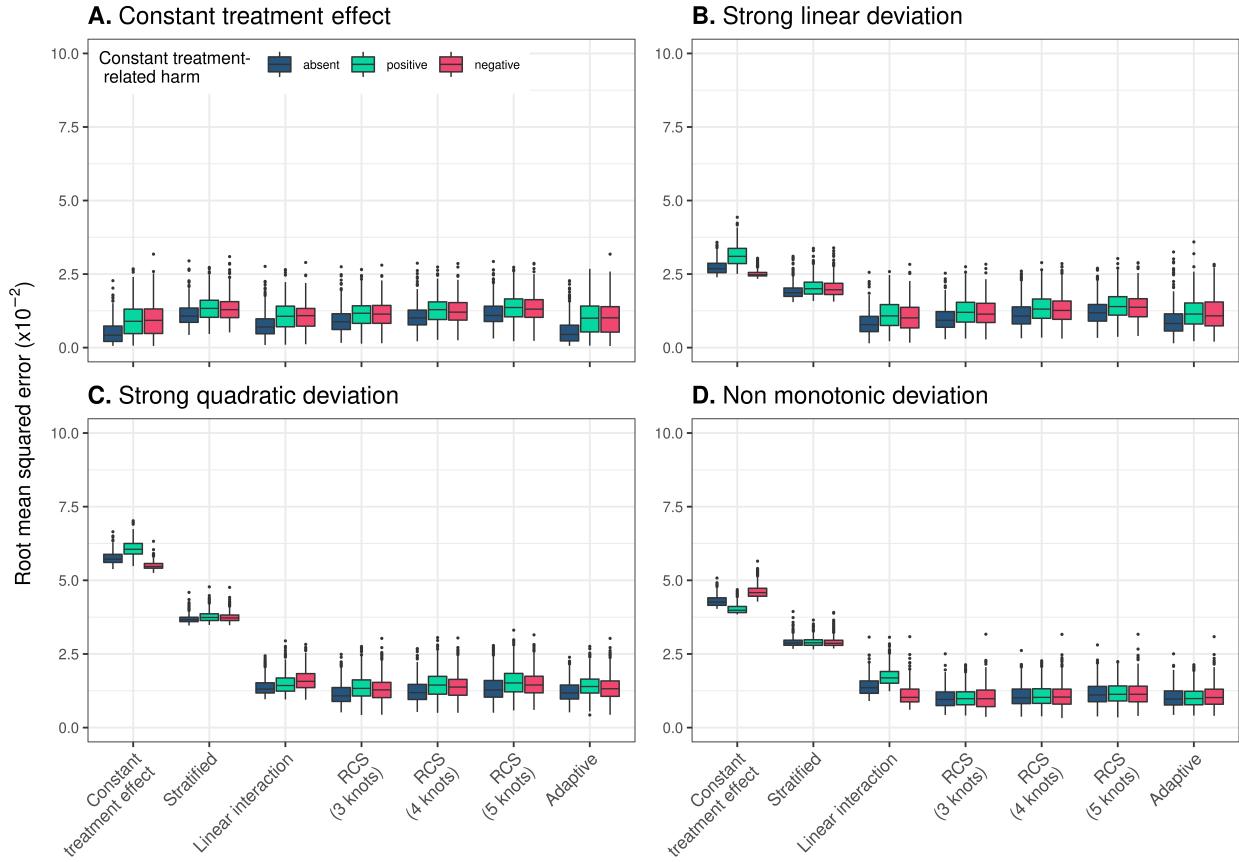


Figure 2: RMSE of the considered methods across 500 replications calculated in a simulated sample of size 500,000. Sample size 17,000 rather than 4250 in Figure 1

- 1 complex models compared to the base case scenario. In the case of strong linear deviations, the linear interaction
 2 model was selected the majority of the time (63%), while the simpler constant treatment effect model was selected
 3 26% of the time (Supplementart Table S7). However, the increased RMSE of the constant treatment effect model
 4 inflated the the RMSE of the linear interaction model. In the case of strong quadratic deviations the RCS (3
 5 knots) model was selected 84% of the time.
- 6 The constant effects model, the linear interaction model and models with RCS smoothing (3 knots) had the
 7 highest median c-for-benefit in the base case scenario and the scenarios where linear and quadratic deviations
 8 were considered. The constant treatment effect model and the linear interaction model tended to present much
 9 lower variability compared to all other approaches (Figure 4). With increasing number of RCS knots, we observed
 10 decreasing median values and increasing variability of the c-for-benefit in all scenarios.
- 11 As for calibration, the linear interaction model had the lowest median ICI-for-benefit in the majority of scenarios
 12 except for the scenarios where no or moderate linear deviations from the base case were considered. In that case
 13 constant treatment effect models demonstrated optimal calibration, very comparable to the linear interaction

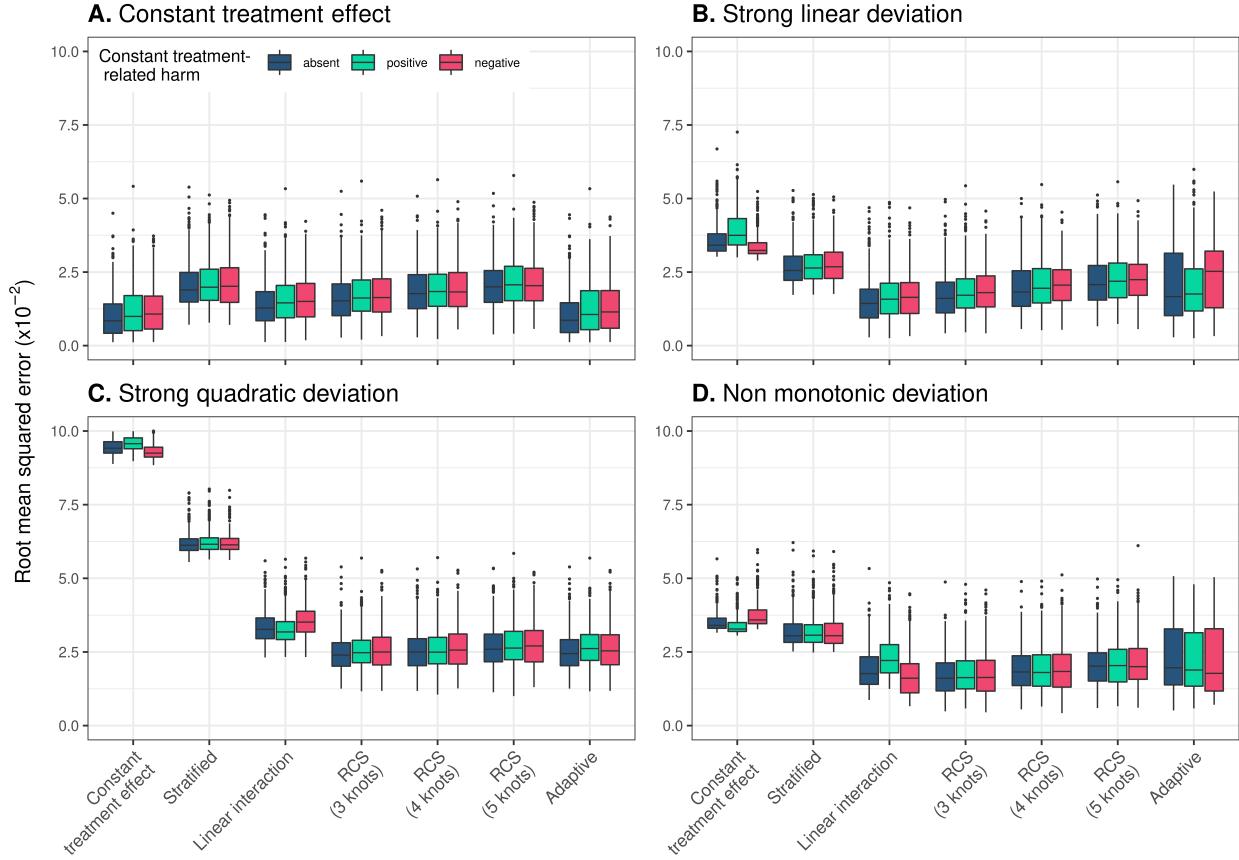


Figure 3: RMSE of the considered methods across 500 replications calculated in a simulated sample of size 500,000. True prediction AUC of 0.85 and sample size of 4,250.

1 model's performance, nonetheless (Figure 5). With strong linear or quadratic deviations, the constant treatment
 2 effect model was poorly calibrated (Figure 5; Panels C and D).

3 3.2 Case study

4 We demonstrate the different methods for individualizing treatment benefits using data from 30,510 patients with
 5 an acute myocardial infarction (MI) included in the GUSTO-I trial. 10,348 patients were randomized to tissue
 6 plasminogen activator (tPA) treatment and 20,162 were randomized to streptokinase. The outcome of interest
 7 was 30-day mortality, recorded for all patients.

8 In line with previous analyses [10,11], we fitted a logistic regression model with 6 baseline covariates, i.e. age,
 9 Killip class, systolic blood pressure, heart rate, an indicator of previous MI, and the location of MI, to predict
 10 30-day mortality risk. A constant effect of treatment was included in the model. When deriving risk predictions
 11 for individuals we set the treatment indicator to 0. More information on model development can be found in the
 12 supplement.

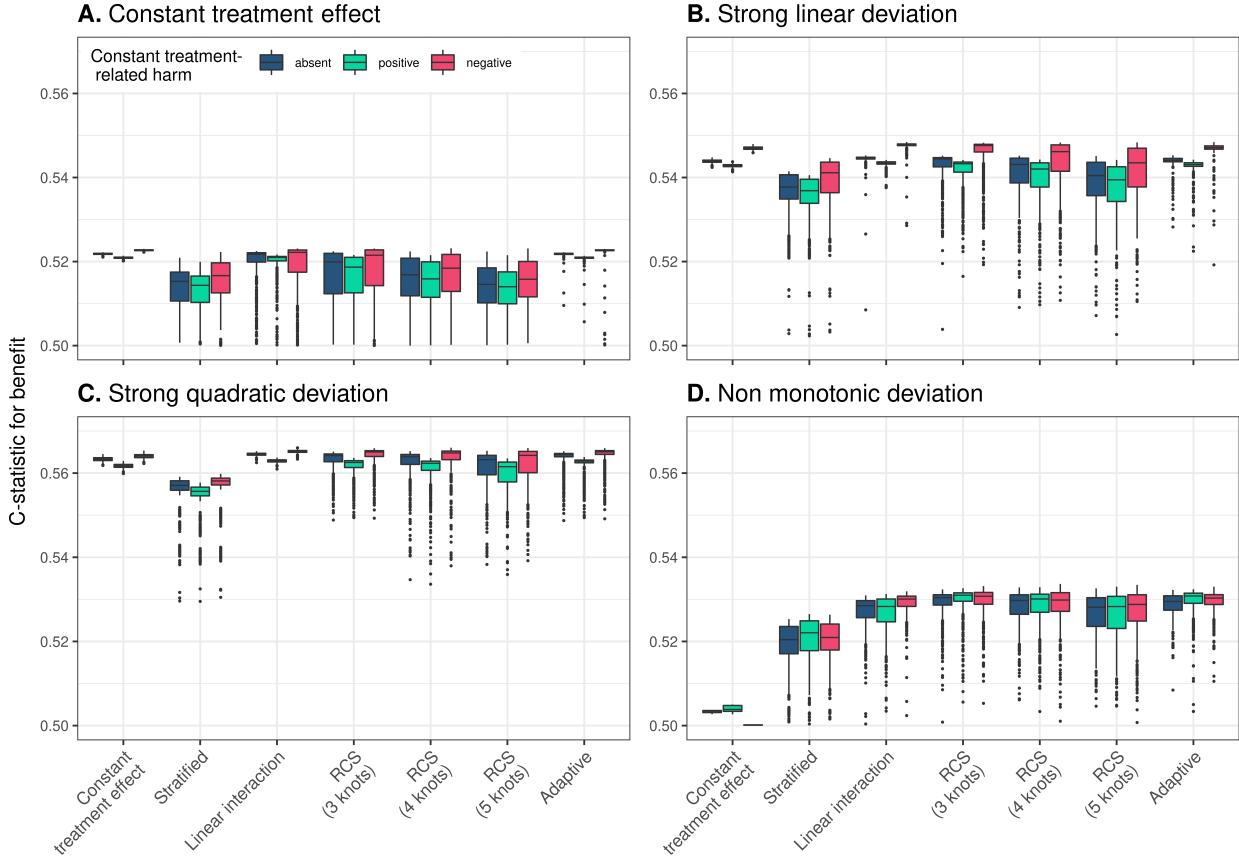


Figure 4: Discrimination for benefit of the considered methods across 500 replications calculated in a simulated sample of size 500,000. True prediction AUC of 0.75 and sample size of 4,250.

We used the risk linear predictor to fit the proposed methods under study for individualizing absolute benefit predictions. All methods predicted increasing benefits for patients with higher baseline risk predictions, but the fitted patterns were clearly different. The adaptive approach selected the model with RCS smoothing with 4 knots. However, for very low baseline risk this model predicted decreasing benefit with increasing risk may be somewhat too flexible. The more robust models, the linear interaction model or the model with RCS smoothing (3 knots), gave very similar benefit predictions, followed the evolution of the stratified estimates very closely and may therefore be preferable for use in clinical practice. The linear interaction model had somewhat lower AIC compared to the model with RCS smoothing (3 knots), slightly better cross-validated discrimination (c-for-benefit 0.526 vs 0.525) and quite similar cross-validated calibration (ICI-for benefit 0.0115 vs 0.0117).

4 Discussion

The linear interaction model proved to be superior to alternative approaches when predicting risk-based treatment benefit under a wide range of scenarios. It generally had lower mean squared error, lower e-for-benefit and higher c-for-benefit with lower variability across simulation replications. Models including restricted cubic splines with

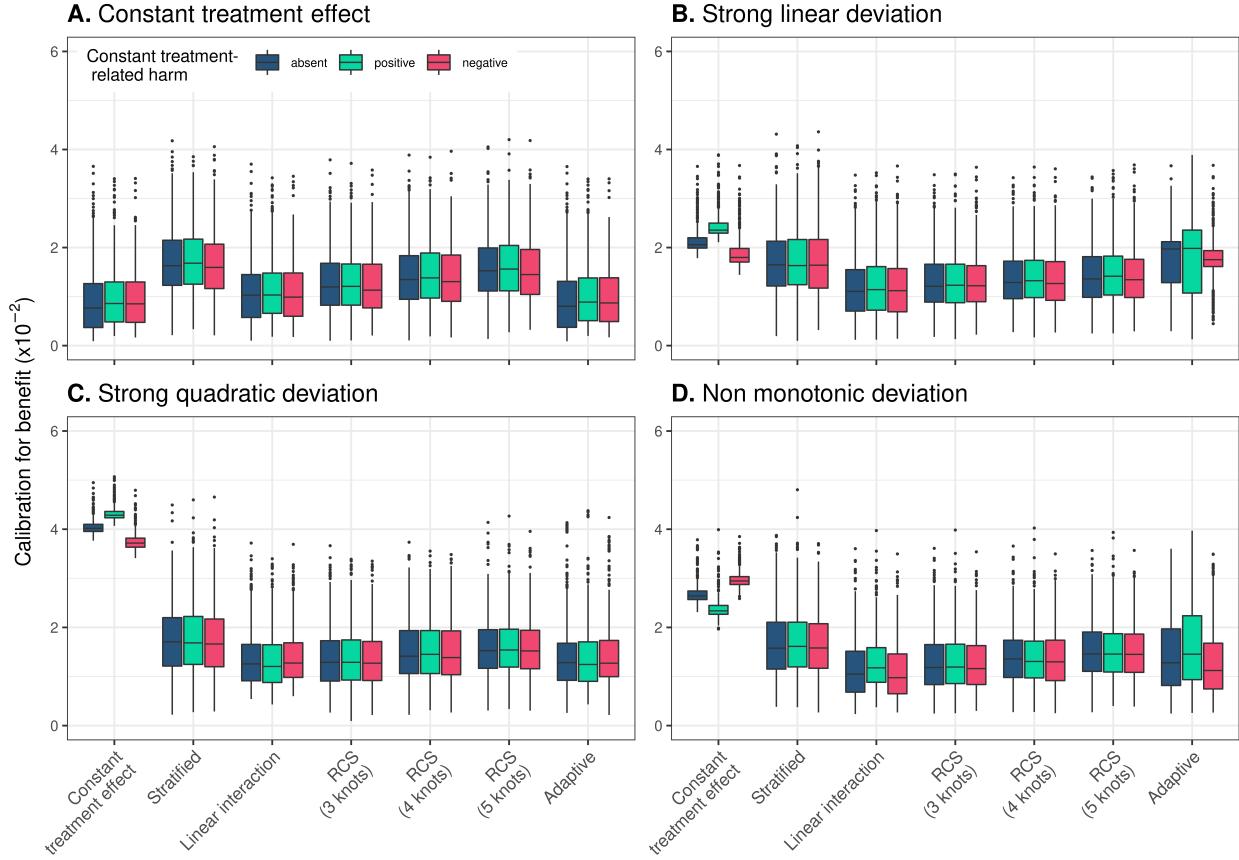


Figure 5: Calibration for benefit of the considered methods across 500 replications calculated in a simulated sample of size 500,000. True prediction AUC of 0.75 and sample size of 4,250.

- 1 3 knots only outperformed the linear interaction model in the presence of strong quadratic deviations from a
- 2 constant relative treatment effect.
- 3 Models including restricted cubic splines with 4 or 5 knots proved to be too flexible, as indicated by higher RMSE,
- 4 increased variability of discrimination for benefit and worse calibration of benefit predictions. Even with larger
- 5 sample sizes and strong quadratic deviations from the base case scenario of constant relative treatment effects,
- 6 these more flexible restricted cubic splines did not outperform the simpler RCS with 3 knots. These approaches
- 7 may only be helpful if we expect more extreme patterns of heterogeneous treatment effects compared to the
- 8 quadratic deviations considered here.
- 9 The constant treatment effect model, despite having adequate performance in the presence of weak treatment
- 10 effect heterogeneity on the relative scale, quickly broke down with stronger deviations from constant relative
- 11 treatment effects. In these cases, the stratified approach generally had lower error rates compared to the constant
- 12 treatment effect model. Stepwise treatment benefit estimates are very useful for demonstrating treatment effect
- 13 heterogeneity—because estimating treatment effect requires groups of patients rather than individual patients—but
- 14 are not helpful for making individualized absolute benefit predictions.

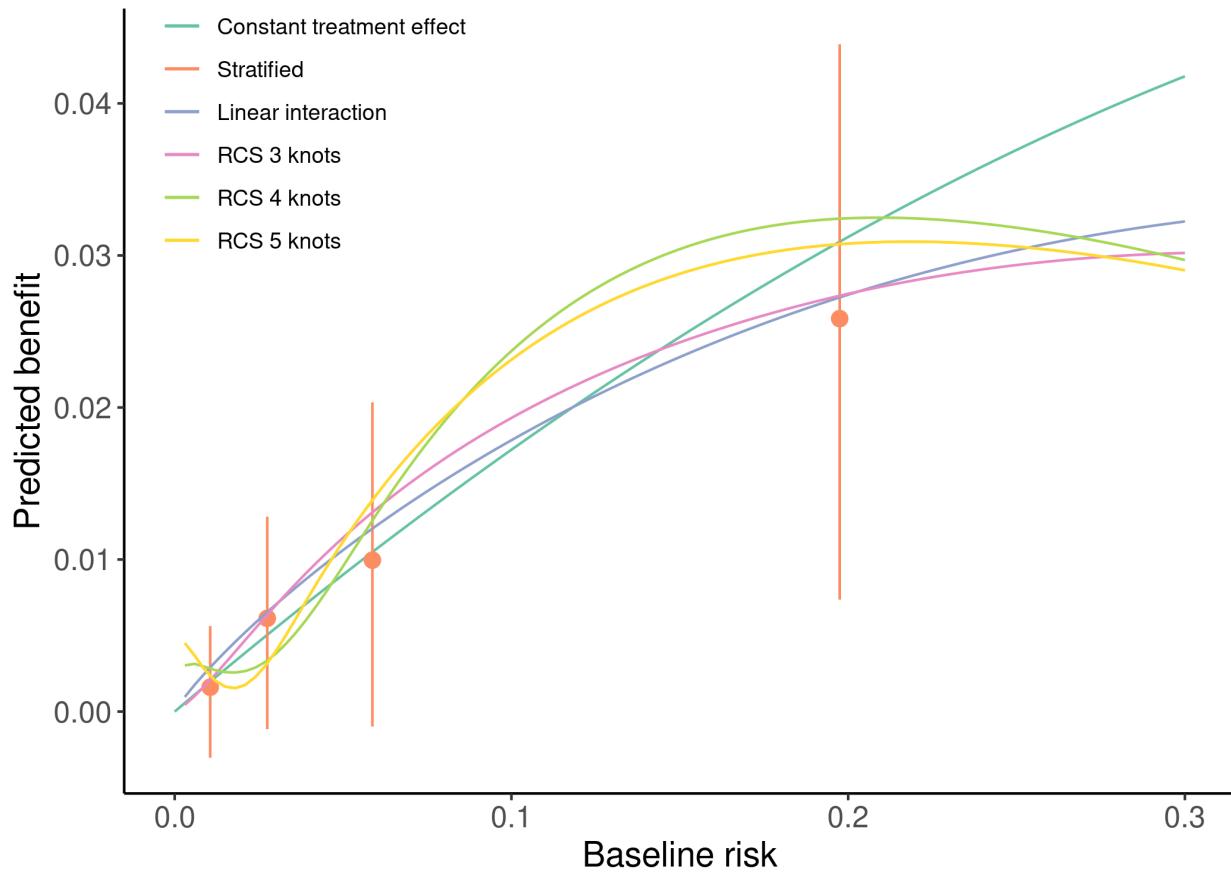


Figure 6: Individualized absolute benefit predictions based on baseline risk when using a constant treatment effect approach, a linear interaction approach and RCS smoothing using 3,4 and 5 knots. Risk stratified estimates of absolute benefit are presented within quartiles of baseline risk as reference.

- 1 Increasing the discriminative ability of the risk model—by increasing the predictor coefficients of the true risk
- 2 model-reduced RMSE for all methods. This increase in discriminative ability translates in higher variability of
- 3 predicted risks, which, in turn, allows the considered methods to better capture absolute treatment benefits. As
- 4 a consequence, the increase in discriminative ability of the risk model also led to higher values of c-for-benefit.
- 5 Even though risk model performance is very important for the ability of risk-based methods to predict treatment
- 6 benefit, prediction model development was outside the scope of this work and has already been studied extensively
- 7 [5,12,13].
- 8 The adaptive approach had adequate performance, following closely the performance of the “true” model in most
- 9 scenarios. However, with smaller sample sizes it tended to “miss” the treatment-risk interactions and selected
- 10 simpler models (Supplementary Table S7). This resulted in increased RMSE variability in these scenarios, especially
- 11 in the case of true strong linear deviations from the base case scenario. This tendency was mitigated when the
- 12 discriminative ability of the prediction model was higher. Therefore, in the case of smaller sample sizes and/or
- 13 poorly discriminating prediction models, the simpler linear interaction model is a safer choice for predicting absolute
- 14 benefits.

1 Risk-based approaches to predictive HTE estimate treatment benefit as a function of baseline risk. A limitation of
2 our study is that we assumed treatment benefit to be a function of baseline risk in the majority of the simulation
3 scenarios. Nevertheless, our main conclusions did not change when we generated individual treatment-covariate
4 interactions (supplementary table/figure x). Future simulation studies could explore the effect of more extensive
5 deviations from risk-based treatment effects.

6 Recent years have seen an increased interest in predictive HTE approaches focusing on individualized benefit
7 predictions. In our simulations we only focused on risk-based methods, using baseline risk as a reference in a
8 two-stage approach to individualizing benefit predictions. However, there is a plethora of different methods, ranging
9 from treatment effect modeling to tree-based approaches available in more recent literature [14–16]. Simulations
10 are also needed to assess relative performance and define the settings where these break down or outperform each
11 other.

12 In conclusion, when comparing different risk-based approaches to predicting individualized treatment benefit, a
13 model including a linear treatment interaction with the prognostic index performed best in a wide range of scenarios.
14 More flexible models with restricted cubic splines required larger sample sizes and higher AUC of the prognostic
15 index to outperform the linear interaction model. An adaptive approach, selecting the model with the optimal AIC,
16 had comparable performance to the best performing approach in most of the scenarios.

1 5 References

- 2 [1] Varadhan R, Segal JB, Boyd CM, Wu AW, Weiss CO. A framework for the analysis of heterogeneity of
3 treatment effect in patient-centered outcomes research. *Journal of Clinical Epidemiology* 2013;66:818–25.
4 <https://doi.org/10.1016/j.jclinepi.2013.02.009>.
- 5 [2] Rekkas A, Paulus JK, Raman G, Wong JB, Steyerberg EW, Rijnbeek PR, et al. Predictive approaches
6 to heterogeneous treatment effects: A scoping review. *BMC Medical Research Methodology* 2020;20.
7 <https://doi.org/10.1186/s12874-020-01145-1>.
- 8 [3] Kent DM, Paulus JK, Klaveren D van, D'Agostino R, Goodman S, Hayward R, et al. The predictive
9 approaches to treatment effect heterogeneity (PATH) statement. *Annals of Internal Medicine* 2019;172:35.
10 <https://doi.org/10.7326/m18-3667>.
- 11 [4] Kent DM, Klaveren D van, Paulus JK, D'Agostino R, Goodman S, Hayward R, et al. The predictive approaches
12 to treatment effect heterogeneity (PATH) statement: Explanation and elaboration. *Annals of Internal Medicine*
13 2019;172:W1. <https://doi.org/10.7326/m18-3668>.
- 14 [5] Klaveren D van, Balan TA, Steyerberg EW, Kent DM. Models with interactions overestimated heterogeneity of
15 treatment effects and were prone to treatment mistargeting. *Journal of Clinical Epidemiology* 2019;114:72–83.
16 <https://doi.org/10.1016/j.jclinepi.2019.05.029>.
- 17 [6] Kent DM, Rothwell PM, Ioannidis JP, Altman DG, Hayward RA. Assessing and reporting heterogeneity in treat-
18 ment effects in clinical trials: A proposal. *Trials* 2010;11. <https://doi.org/10.1186/1745-6215-11-85>.
- 19 [7] Harrell FE, Lee KL, Pollock BG. Regression models in clinical studies: Determining relationships between
20 predictors and response. *JNCI Journal of the National Cancer Institute* 1988;80:1198–202. <https://doi.org/10.1093/jnci/80.15.1198>.
- 22 [8] Klaveren D van, Steyerberg EW, Serruys PW, Kent DM. The proposed “concordance-statistic for benefit”
23 provided a useful metric when modeling heterogeneous treatment effects. *Journal of Clinical Epidemiology*
24 2018;94:59–68. <https://doi.org/10.1016/j.jclinepi.2017.10.021>.
- 25 [9] Austin PC, Steyerberg EW. The integrated calibration index (ICI) and related metrics for quantifying the
26 calibration of logistic regression models. *Statistics in Medicine* 2019;38:4051–65. <https://doi.org/10.1002/sim.8281>.
- 28 [10] Califf RM, Woodlief LH, Harrell FE, Lee KL, White HD, Guerci A, et al. Selection of thrombolytic
29 therapy for individual patients: Development of a clinical model. *American Heart Journal* 1997;133:630–9.
30 [https://doi.org/10.1016/s0002-8703\(97\)70164-9](https://doi.org/10.1016/s0002-8703(97)70164-9).

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- 1 [11] Steyerberg EW, Bossuyt PMM, Lee KL. Clinical trials in acute myocardial infarction: Should we ad-
2 just for baseline characteristics? *American Heart Journal* 2000;139:745–51. [https://doi.org/10.1016/s0002-8703\(00\)90001-2](https://doi.org/10.1016/s0002-8703(00)90001-2).
- 4 [12] Burke JF, Hayward RA, Nelson JP, Kent DM. Using internally developed risk models to assess heterogeneity
5 in treatment effects in clinical trials. *Circulation: Cardiovascular Quality and Outcomes* 2014;7:163–9.
6 <https://doi.org/10.1161/circoutcomes.113.000497>.
- 7 [13] Abadie A, Chingos MM, West MR. Endogenous stratification in randomized experiments. *The Review of
8 Economics and Statistics* 2018;100:567–80. https://doi.org/10.1162/rest_a_00732.
- 9 [14] Athey S, Tibshirani J, Wager S. Generalized random forests. *The Annals of Statistics* 2019;47. <https://doi.org/10.1214/18-aos1709>.
- 11 [15] Lu M, Sadiq S, Feaster DJ, Ishwaran H. Estimating individual treatment effect in observational data
12 using random forest methods. *Journal of Computational and Graphical Statistics* 2018;27:209–19. <https://doi.org/10.1080/10618600.2017.1356325>.
- 14 [16] Wager S, Athey S. Estimation and inference of heterogeneous treatment effects using random forests. *Journal
15 of the American Statistical Association* 2018;113:1228–42. <https://doi.org/10.1080/01621459.2017.1319839>.