Supplemental Materials

Part A Important Symbol Glossary in the Manuscripts.

Table1. Important Symbol Glossary:

Notion	Annotation
RWD	Real world data
ETD	External trial data
CTD	Current trial data
MAP	The meta-analytic-predictive prior
rMAP	A robust MAP prior.
EB-rMAP	Empirical Bayes robust MAP prior method
SAM	The self-adapting mixture prior
PPCM	Prior-Posterior Consistency Measure the proposed method in the paper
S	The number of propensity scores stratification.
K	The number of time intervals in piecewise exponential model.
$r, r_k, r_{s,k}$, $r_{ETD,s,k}, r_{RWD,s,k}, r_{CTD,s,k}$	The number of events, the number of events in k-th time interval, the number of events in s-th stratrum and k-th time interval, $r_{s,k}$ of external trial data, $r_{s,k}$ of real-world data, $r_{s,k}$ of current trial data.
$E, E_k, E_{s,k}$, $E_{ETD,s,k}, E_{RWD,s,k}, E_{CTD,s,k}$	The total observation time, including the censoring times $E_k = \sum_{i=1}^{n_k} t_{ik}$ (t_{ik} denotes the event time of patient i in the k-th interval), E_k in s-th stratrum, $E_{s,k}$ of external trial data, $E_{s,k}$ of real-world data, $E_{s,k}$ of current trial data.
$\lambda, \lambda_k, \lambda_{s,k}$, $\lambda_{ETD,s,k}, \lambda_{RWD,s,k}, \lambda_{CTD,s,k}$	The hazard rate of patients, the hazard rate in k-th time interval, λ_k in s-th stratrum, $\lambda_{s,k}$ of external trial data, $\lambda_{s,k}$ of real-world data, $\lambda_{s,k}$ of current trial data.
Z, Z_1, Z_2	$Z = (Z_1, Z_2)$ is the study indicator and $Z = (0,0)$ indicates that the patient is from the current RCT study, while $Z = (1,0)$ and $Z = (0,1)$ correspond to patients from the external RCT study and RWD study, respectively.
$\boldsymbol{X}$	Denote the vector of covariates.

Table1 (continue). Important Symbol Glossary:

Notion	Annotation
$e(X)$	The propensity score was defined as the probability that a patient belongs to current trial data.
$\epsilon, \epsilon_k, \epsilon_{s,k}$, $\epsilon_{ETD,s,k}, \epsilon_{RWD,s,k}, \epsilon_{CTD,s,k}$	The consistency measure between historical data and current trial data, the consistency measure in k-th time interval, ϵ_k in s-th stratrum, $\epsilon_{s,k}$ of external trial data, $\epsilon_{s,k}$ of real-world data, $\epsilon_{s,k}$ of current trial data.
$D_{CTD}, D_{ETD}, D_{RWD} D_{HD}$	The variables represent the data set from current trial data, external trial data, real-world data, while $D_{HD} = \{D_{ETD}, D_{RWD}\}$ represents the historica data.
$d_{CTD}, d_{ETD}, d_{RWD} d_{HD}$	The specific observation dataset corresponds to $D_{CTD}, D_{ETD}, D_{RWD} D_{HD}$.
$n, n_{ETD,k}, n_{RWD,k}, n_{CTD,k}$ $n_{ETD,s,k}, n_{RWD,s,k}, n_{CTD,s,k}$	The sample size of data set, the sample size of external trial data in k-th time interval, the sample size of current trial data in k-th time interval, the sample size of real-world data in k-th time interval, $n_{ETD,k}$, $n_{RWD,k}$, $n_{CTD,k}$ in s-th stratrum.
ESS	Effective sample size
$\delta_{RWD}, \delta_{ETD}$	the baseline difference between real-world data with current trial data, the baseline difference between external trial data with current trial data.
β_{CTD}	Represents the treatment effect between groups in the current trial
$\gamma_{ETD}, \gamma_{RWD}$	γ_{ETD} represents the difference in treatment effects between the external trial and the current trial, and γ_{RWD} represents the difference in treatment effects between real-world data and the current trial.
$group$	group = 1 denotes the treatment group and the other denotes the control group.
$\hat{f}(\lambda_k \| D_{HD})$, $\hat{f}(\lambda_k \| d_{CTD}, d_{HD})$, $\hat{f}(D \| d_{CTD}, d_{HD})$ $F_{D \| d_{CTD}, d_{HD}}(d)$	The prior probability density function of λ_k, the posterior probability density function of λ_k, the posterior predictive density function of data set. the cumulative distribution function of $\hat{f}(D \| d_{CTD}, d_{HD})$.

Table1 (continue). Important Symbol Glossary:

Notion	Annotation
Γ	A parameter in PPCM measure represents the minimum required consistency value during borrowing information.
T1E	The type I error is denoted as T1E
MSE	The mean squared error
Box_{MSDB}, EB_{MSDB}, SAM_{MSDB}	when constructing the prior under the MSDB approach, we replace the robust weight ω_R with one obtained from another method. This allows us to compare the proposed consistency measure with existing methods and demonstrate its advantages. Denote the three comparison methods under this MSDB framework as Box_{MSDB}, EB_{MSDB}, and SAM_{MSDB}.

Part B Multinomial Logistic Regression for Propensity Score Calculation

In observational studies, the use of propensity scores (PS) has become an essential tool to balance confounding factors across treatment groups or data sources, thereby enabling more accurate causal inference. In this study, propensity scores are specifically employed to adjust for baseline differences between data from different sources, such as real-world data (RWD) and external trial data (ETD), ensuring comparability and reducing bias when estimating treatment effects. Given that the treatment assignment in our study involves multiple categories, a multinomial logistic regression model is utilized to calculate propensity scores. This model provides a method to estimate the conditional probability of receiving each treatment group based on a set of observed covariates.

Let Z indicate different data sources, which has k data sources. Let X represent the covariates that are used to predict the data assignment. The multinomial logistic regression model can be written as:

$$ln\left(\frac{P(Z=j|\boldsymbol{X})}{P(Z=k|\boldsymbol{X})}\right)=\boldsymbol{\beta}_j^T\boldsymbol{X} \quad \text{for} \quad j=1,2,\ldots,k-1$$

Where $P(Z=j|X)$ is the probability of being assigned to treatment group j, $P(Z=k|X)$ is the reference group (commonly taken as the baseline group), β_j is the vector of regression coefficients associated with treatment group j relative to the baseline group.

The propensity score is the estimated probability of receiving a specific treatment group, given the observed covariates X. This is derived from the multinomial logistic regression model:

$$P(Z=j|\boldsymbol{X})=\frac{exp\left(\boldsymbol{\beta}_j^T\boldsymbol{X}\right)}{1+\sum_{\mathrm{m}=1}^{\mathrm{k}-1}\mathrm{m}\exp(\boldsymbol{\beta}_m^T\boldsymbol{X})}$$

The derivation from $\frac{P(Z=j|\boldsymbol{X})}{P(Z=k|\boldsymbol{X})}$ to $P(Z=j|\boldsymbol{X})$ follow the steps below:

1.Start with the odds ratio for treatment j relative to the baseline group k:

$$\frac{P(Z=j|\boldsymbol{X})}{P(Z=k|\boldsymbol{X})}=\exp(\boldsymbol{\beta}_j^T\boldsymbol{X})$$

2.Rearrange the equation to express $P(Z=j|\boldsymbol{X})$ in terms of $P(Z=k|\boldsymbol{X})$:

$$\mathrm{P}(Z=j|\boldsymbol{X})=\mathrm{P}(Z=k|\boldsymbol{X})\cdot\exp\left(\boldsymbol{\beta}_{\mathrm{j}}^{\mathrm{T}}\boldsymbol{X}\right)$$

3. Normalize to ensure that the sum of probabilities across all groups equals 1. For k groups, we have:

$$\mathrm{P}(Z = k|\boldsymbol{X}) + \sum_{m=1}^{\mathrm{k}-1} \mathrm{P}(Z = m|\boldsymbol{X}) = 1$$

4. Substitute $P(Z = j|\boldsymbol{X})$ from step 2 into this equation:

$$P(Z = k|\boldsymbol{X}) + \sum_{m=1}^{\boldsymbol{k}-1} (P(Z = k|\boldsymbol{X}) \cdot \exp(\boldsymbol{\beta}_m^T \boldsymbol{X})) = 1$$

5. Factor out $P(Z = k|\boldsymbol{X})$:

$$P(Z = k|\boldsymbol{X}) \left(1 + \sum_{m=1}^{\mathrm{k}-1} \exp\ (\boldsymbol{\beta}_m^T \boldsymbol{X}) \right) = 1$$

6. Solve for $P(Z = k|\boldsymbol{X})$:

$$P(Z = k|\boldsymbol{X}) = \frac{1}{\left(1 + \sum_{m=1}^{k-1} \exp\ (\boldsymbol{\beta}_m^T \boldsymbol{X})\right)}$$

7.Finally, substitute this expression for $P(Z = k|\boldsymbol{X})$ back into the equation for $P(Z = j|\boldsymbol{X})$:

$$P(Z = j|\boldsymbol{X}) = \frac{\exp\left(\boldsymbol{\beta}_j^T \boldsymbol{X}\right)}{\left(1 + \sum_{m=1}^{k-1} \exp\ (\boldsymbol{\beta}_m^T \boldsymbol{X})\right)}$$

In this paper $Z = j$ is equivalent to $Z_1 = (0,1)$ or $Z_2 = (1,0)$ and $Z = k$ is equivalent to $Z_0 = (0,0)$ therefore the formula for calculating the propensity score shown in the main manuscript can be obtained.

Part C The calculation of $\epsilon_{RWD,s,k}$ and $\epsilon_{ETD,s,k}$ in section 2.2.2

The values $\epsilon_{RWD,s,k}$ and $\epsilon_{ETD,s,k}$, which serve as measures of the consistency between real-world data or external RCT data and the current trial, are also calculated based on the PPCM metric proposed in this paper. The approach is to transform one of the two compared data into prior, so as to construct a consistency measure based on the posterior predictive function. As described in the main text, within stratum s of the propensity score stratification and time interval k, the total exposure time follows a Gamma distribution parameterized by the total number of events and the hazard rate.

$$E_{ETD,s,k} \sim Gamma(r_{ETD,s,k}, \lambda_{ETD,s,k})$$

Given a vague prior $\lambda_{ETD,s,k} \sim Gamma(0.01,0.01)$ for $\lambda_{ETD,s,k}$, the posterior distribution can then be obtained:

$$\begin{aligned} f(\lambda_{s,k} | r_{ETD,s,k}, E_{ETD,s,k}) &\propto p(E_{ETD,s,k} | r_{ETD,s,k}, \lambda_{ETD,s,k}) \cdot f(\lambda_{ETD,s,k}) \\ &\propto \lambda_{ETD,s,k}^{r_{ETD,s,k}} e^{-\lambda_{ETD,s,k} E_{ETD,s,k}} \cdot \lambda_{ETD,s,k}^{0.01-1} e^{-0.01\lambda_{ETD,s,k}} \\ &= \lambda_{ETD,s,k}^{r_{ETD,s,k}+0.01-1} e^{-\lambda_{ETD,s,k}(E_{ETD,s,k}+0.01)} \end{aligned}$$

Therefore, the hazard rate $\lambda_{ETD,s,k}$ of the external RCT data in stratum s and time interval k is equivalent to following the following posterior distribution:

$$\lambda_{ETD,s,k} | r_{ETD,s,k}, E_{ETD,s,k} \sim Gamma(r_{ETD,s,k} + 0.01, E_{ETD,s,k} + 0.01)$$

By treating this distribution as the prior for the parameter$\lambda_{CTD,s,k}$ of the current trial data, the posterior distribution can then be derived as follows:

$$f(\lambda_{CTD,s,k} | d_{CTD,s,k}, d_{ETD,s,k}) \propto p(E_{CTD,s,k} | r_{CTD,s,k}, \lambda_{CTD,s,k}) \cdot f(\lambda_{CTD,s,k} | r_{ETD,s,k}, E_{ETD,s,k})$$

Equivalently, there is the posterior distribution for $\lambda_{CTD,s,k}$ as follows

$$\lambda_{CTD,s,k} | d_{CTD,s,k}, d_{ETD,s,k} \sim Gamma(r_{CTD,s,k} + r_{ETD,s,k} + 0.01, E_{ETD,s,k} + E_{ETD,s,k} + 0.01)$$

Therefore, according to Bayesian theory, jointing sample likelihood function can infer the sample posterior predictive probability distribution as

$$\begin{aligned} & f(D | d_{CTD,s,k}, d_{ETD,s,k}) = \int f(E_{s,k} | r_{s,k}, \lambda_{s,k}) f(\lambda_{s,k} | d_{CTD,s,k}, d_{ETD,s,k}) d\lambda_{s,k} \\ & = \int Gamma(r_{s,k}, \lambda_{s,k}) Gamma(r_{CTD,s,k} + r_{ETD,s,k} + 0.01, E_{ETD,s,k} + E_{z,s,k} + 0.01)\, d\lambda_{s,k} \end{aligned}$$

The cumulative distribution function corresponding to the posterior predictive probability distribution is:

$$F(D|d_{CTD,s,k},d_{ETD,s,k}) = \int_0^D f(d|d_{CTD,s,k},d_{ETD,s,k})\mathrm{d}d$$

$$= \int_0^{E_{s,k}} \int f(e_{s,k}|r_{s,k},\lambda_{s,k}) f(\lambda_{s,k}|d_{CTD,s,k},d_{ETD,s,k}) d\lambda_{s,k}\, de_{s,k}$$

$$= \int_0^{E_{s,k}} \int Gamma\,(r_{s,k},\lambda_{s,k}) Gamma(r_{CTD\,,s,k} + r_{ETD\,,s,k} + 0.01, E_{CTD\,,s,k} + E_{ETD\,,s,k} + 0.01)\, d\lambda_{s,k} de_{s,k}$$

However, there is no analytical solution for this cumulative distribution function, so it is approximated in this paper by Monte Carlo simulations

Based on the definition of PPCM, we can get the consistency estimate of the current trial data and the external trial data as:

$$\epsilon_{ETD,s,k} = 2 * min\{F(d_{CTD,s,k}|d_{CTD,s,k},d_{ETD,s,k}),\ 1 - F(d_{CTD,s,k}|d_{CTD,s,k},d_{ETD,s,k})\}$$

Similarly we can obtain estimates of the consistency of real-world data with current trial data.

Part D Theoretical details of extending the MSDB prior to studies with more than three sources of external data

Let X denote the vector of covariates, and $\mathrm{z} = 0,1, \ldots, \mathrm{Z}(\mathrm{Z} \geq 3)$ indicate the data source. Specifically, $\mathrm{Z} = 0$ corresponds to the current trial data, while $\mathrm{Z} \geq 1$ represents historical datasources, including external trial data and real-world data.

Step 1: propensity scores stratification.

Define propensity score $\mathrm{e}(\mathrm{X})$ as the probability that a patient belongs to current trial data modeled by multinomial logistic regression:

$$ln\left\{\frac{P(z=j)}{P(z=0)}\right\} = \beta_{0,j} + \beta_{1,j}x_1 + \beta_{2,j}x_2 + \cdots + \beta_{p,j}x_p, \mathrm{j} \geq 1$$

p was the number of covariables and employing maximum likelihood estimation give the $e(X)$ as follows:

$$\hat{e}(X) = P(z=0|X) = \frac{1}{1 + \sum_{z=1}^{Z} exp\left(\widehat{\beta_{0,z}} + \sum_p \widehat{\beta_{p,z}} x_p\right)}$$

Let $Q = \{q_0 < q_1 < \cdots < q_s\}$ be the set of quantiles used to form S strata according to propensity score $\hat{e}(X)$, ensuring an approximately equal number of patients from the current RCT in each stratum. Similarly, external trial data and real world data were stratified with patients outside q_0 and q_S trimmed.

Step 2: Stratum-specific MAP prior in k-th time intervals.

In this step, the MAP framework integrates the historical data into a prior distribution. Given the use of propensity score stratification and piecewise exponential model, the S strata and K intervals must be modeled separately. In this study, the data are assumed to follow a piecewise exponential model. Consequently, the total observation time E follows a gamma distribution, where the shape parameter corresponds to the number of events r and the scale parameter corresponds to the hazard rate λ. Following the MAP framework, we have:

$$E_{z,s,k} \sim Gamma\left(r_{z,s,k}, \lambda_{z,s,k}\right)$$

$$\log\lambda_{z,s,k} \sim N\left(\mu_{z,s,k}, \tau_{z,s,k}^2\right)$$

$$z = 1, \ldots, Z; s = 1, \ldots, S; k = 1, \ldots, K$$

Using a full Bayesian approach, the distribution of the hyper-parameters $log\mu_{z,s,k}$, $\tau^2_{z,s,k}$ must be specified. Weakly-informative normal priors are chosen for $\mu_{z,s,k}$ with a mean μ_0 and a large variance, for example, $\sigma_0^2 = 1000$. The half-normal prior is chosen for the $\tau^2_{z,s,k}$ with $\sigma_\tau^2 = \frac{\epsilon_{ref}}{\epsilon_{z,s,k}}$, where $\epsilon_{z,s,k}$ are derived using the PPCM measure and ϵ_{ref} is the median of $\epsilon_{z,s,k}$.

$$\lambda_{z,s,k} \sim Gamma\left(r_{z,s,k}, E_{z,s,k}\right)$$

$$\widehat{f}\left(\lambda_{s,k} \middle| d_{z=0}, d_{z=j}\right) \propto Gamma(r_{z=0,s,k} + r_{z=j,s,k}, E_{z=0,s,k} + E_{z=j,s,k})$$

$$\hat{f}(D|d_{z=0}, d_{z=j}) = \int f(E_{s,k}|r_{s,k}, \lambda_{s,k})\widehat{f}\,(\lambda_{s,k}|d_{z=0}, d_{z=j})d\lambda_{s,k}$$

$$F(D) = \int_0^E \hat{f}\left(D\middle|d_{z=0}, d_{z=j}\right)de$$

$$= \int_0^{E_{s,k}} \int f(e_{s,k}|r_{s,k}, \lambda_{s,k})\widehat{f}\,(\lambda_{s,k}|d_{z=0}, d_{z=j})d\lambda_{s,k}\, de_{s,k}$$

$$\epsilon_{z=j,s,k} = 2 * min\{F(d_{z=0}), 1 - F(d_{z=j})\}$$

Step 3: Integrating the prior information in each time intervals.

Once the prior distributions of $\lambda_{z,s,k}$ were obtained, they were merged by considering the heterogeneity between the studies. This process was conducted as follows.

$$\lambda_{s,k} = \sum\nolimits_z \omega_{z,s,k} * \lambda_{z,s,k}\,;\ \omega_{z,s,k} = \frac{n_{z,s,k} * \epsilon_{z,s,k}}{\sum_z n_{z,s,k} * \epsilon_{z,s,k}}$$

These weights consider both the sample size and the consistency between the data, allowing more information to be borrowed from historical data with a larger sample size and greater consistency. Once the stratum-specific MAP priors are obtained, the overall prior distribution for K time intervals can be defined using the weights based on the sample sizes n as follows:

$$\lambda_k = \sum_{s=1}^{S} \frac{n_{CTD,s,k}}{n_{CTD,k}} \lambda_{s,k}$$

Step 4: The parametric density estimate of the MAP prior.

The extension of the MSDB prior to cases with three or more external sources follows the same theoretical expressions as that for two sources in the main text; thus, the derivation is not repeated here.

Part E Theoretical Derivations of Comparator Methods for Survival Data

The theoretical introduction of the following methods is based on the piecewise exponential model, which serves as the foundation for applying these approaches to survival outcomes. To facilitate understanding, we begin with the more fundamental MAP prior and emphasize the theoretical similarities and differences among the methods. For consistency, the notation used in this section is aligned with that in the main manuscript.

1. Meta-analytical-predictive prior (MAP prior)[1]

In this study, the data are assumed to follow a piecewise exponential model. Denote $E_{z,k}$ the total observation time for trial z in interval k. Denote $r_{z,k}$ the number of events and $\lambda_{z,k}$ the hazard rate for trial z in interval k respectively. A hierarchical model is formed in the original MAP prior.

1. (Sampling models of data) For $z = 1, \ldots, Z, k = 1, \ldots, K$, $E_{z,k} \sim Gamma\left(r_{z,k}, \lambda_{z,k}\right)$. The sampling models are trial-specific.
2. (Exchangeablility) A normal distribution is assumed for log hazard rate:
$$log\lambda_{1,k}, \ldots, log\lambda_{z,k} \sim N(log\mu_k, \tau_k^2);\ z = 1, \ldots, \mathrm{Z};\ \mathrm{k} = 1, \ldots, \mathrm{K}$$
3. (Hyper-priors) Weakly-informative normal priors are chosen for $log\mu_k$ with a mean μ_0 and a large variance, for example, $\sigma_0^2 = 1000$. On the other hand, the exchangeability parameter τ_k^2 measures ther between-trail heterogeneity and thus regulates the extent of borrowing. Common choices of priors are inverse-gamma distribution for τ_k^2 and half-normal/t families for τ_k

The original MAP prior, $f_{MAP}(\lambda_k | d_{HD})$, derived from the hierarchical model is conditional on historical data only. The challenge, however, is that the MAP prior $f_{MAP}(\lambda_k)$ is usually from an unknown distribution, which means it is difficult to directly sample from $f_{MAP}(\lambda_k)$ in Bayesian computation. With an MCMC sample from$f_{MAP}(\lambda_k)$, the authors chose to replace $f_{MAP}(\lambda_k)$ with its approximation that is based on the results by Dalal and Hall. It was stated that any parametric prior can be satisfactorily approximated by a mixture of conjugate priors. Thus, $f_{MAP}(\lambda_k)$ can be approximated by a weighted mixture of J gamma distributions:

$$\hat{f}_{MAP}(\lambda_k | D_{HD}) = \sum_{j=1}^{J} \omega_j Gamma\left(a_j, b_j\right)$$

where $\sum_{j=1}^{J} \omega_j = 1$. The number of components J is up to the number of data sets, and the other parameters ω_j, a_j, b_j are estimated by the EM algorithm.

2. Robust MAP prior (rMAP prior)[2]

Schmidli and colleagues5 proposed the robust MAP prior that can improve the operating characteristics of MAP prior in the presence of prior-data conflict. The idea is to add a vague prior component to $f_{MAP}(\lambda_k)$ to hedge the situation in which considerable heterogeneity is observed between current and historical data:

$$\begin{aligned}\hat{f}_{rMAP}(\lambda_k|D_{HD}) &= (1-\omega_R)\cdot f_{MAP}(\lambda_k) + \omega_R f_0(\lambda_k)\\ &= (1-\omega_R)\sum_{j=1}^{J}\omega_j Gamma(a_j, b_j) + \omega_R Gamma(a_0, b_0)\end{aligned}$$

where $\omega_R \in [0,1]$. The general principle is to set ω_R close to 0 if the historical data is believed to be "similar with" current data, or vice versa. When $\omega_R = 0$, the rMAP prior reduces to the original MAP prior. On the other hand, it becomes the vague prior when $\omega_R = 1$. A practical challenge in implementing the robust MAP prior is to properly specify the mixture weight ω_R.

3. Empirical bayes robust MAP prior (EB-rMAP prior)[3]

Hongtao Zhang et al. propose a novel empirical Bayes robust MAP prior framework that allows borrowing historical data in an adaptive manner. The EB-rMAP prior is primarily based on the use of the prior predictive p-value (*ppp*) as a consistency measure to inform the data-driven estimation of the mixture weight of rMAP prior. Let T(·) be a statistic of current trial data D_{CTD}, the two-sided prior predictive p-value in its most general form is defined as

$$ppp(d_1) = 2 * min\{Pr_{D_{CTD}|d_{HD}}(T(D_{CTD}) \geq T(d_{CTD})), Pr_{D_{CTD}|d_{HD}}(T(D_{CTD}) \leq T(d_{CTD}))\}$$

Where $Pr_{D_{CTD}|d_{HD}}(\cdot)$ is the predictive distribution of D_{CTD} given historical data d_0. The corresponding predictive distribution of $T(D_{CTD})$ is

$$\mathrm{f}(T(D_{CTD})) = \int f(T(D_{CTD})|\lambda_k)\hat{f}_{rMAP}(\lambda_k|D_{HD})d\lambda_k$$

The optimal mixture weight ω_{EB} in EB-rMAP prior can be defined as the smallest value among all ω_R's that lead to a reasonably large *ppp*. Since a small *ppp* indicates strong prior-data conflict, author recommend setting the threshold to a large value in principle. On the other hand, if *ppp* never exceeds γ, ω_{EB} is then set to 1. This happens when observed current data is very different from historical data. Specifically, we have

$$\omega_{EB} = \begin{Bmatrix} min_{\omega_R}\{\omega_R: ppp(d_{CTD}) \geq \gamma\}, if\,\exists\omega_R\; s.t.\, ppp(d_{CTD}) \geq \gamma \\ 1 \qquad\qquad\qquad\qquad\qquad\qquad ,if\ otherwise \end{Bmatrix}$$

Once ω_{EB} is determined, the EB-rMAP prior is in the form of a weighted mixture of conjugate priors:

$$\begin{aligned}\hat{f}_{EB-rMAP}(\lambda_k|D_{HD}) &= (1-\omega_R)\cdot f_{MAP}(\lambda_k) + \omega_R f_0(\lambda_k) \\ &= (1-\omega_{EB})\sum_{j=1}^{J}\omega_j Gamma(a_j,b_j) + \omega_{EB} Gamma(a_0,b_0)\end{aligned}$$

4. PS-MAP prior[4]

Meizi Liu et al combined a propensity score approach based on the MAP prior to adjust for baseline imbalance. We maintain the same notational definitions as in the main text, with specific technical details as fllows:

Step 1: Estimation of propensity scores

The first step of the PS-integrated MAP prior approach is to estimate patients' propensity scores. The propensity scores $e(X) = Pr(Z = 1|X)$ can be estimated for each patient, where $Z = 1$ if the patient is from the current study, $Z = 0$ if the patient is from external sources.

Step 2: Trimming

Let $\hat{e}(X_i)$ denote the estimated propensity score for patient i. Let $E_1 = \{\hat{e}(X_i): Z_i = 1\}$ be the set of estimated propensity scores of the patients in the current study. To select a subset of patients in pooled external data D_{HD} that are more relevant to the patients in the current study D_{CTD}, patients in the external data source with propensity scores outside the range of E_1 are excluded from the data. The rationale for this trimming step is to remove patients with extreme propensity scores, who are more likely to have strong unmeasured risk factors influencing the observed study assignment.

Step 3: Stratification

Propensity score stratification of the current data together with the external data is performed after trimming the external data. Let $\hat{q}_0 < \hat{q}_1 < \ldots < \hat{q}_S$ be a set of quantiles based on which S propensity score strata are formed. Let $s = 1, \ldots, S$ denhote the sth strarum. Let $D_{s,z} = \{(y_i, X_i): \hat{e}(X_i) \in (\hat{q}_{s-1}, \hat{q}_s]\}$ denote the subset of patients with propensity scores belongs to the sth stratum.

Step 4: Stratum-specific MAP prior

The next step of the proposed method is to apply the MAP prior approach to each of the Sstrata to conduct statistical inference on the stratum-specific parameter of interest. The structure of $Y_{s,z}$ could be modeled by a Bayesian hierarchical model as follows:

$$E_{s,z} \sim Gamma(r_{s,z}, \lambda_{s,z}),$$

$$log\lambda_{s,z} \sim N(\mu_s, \tau_s^2),$$

$$s = 1, \dots, D, Z = 0,1$$

Avagueprior is chosen for the stratum-specific effect μ_s, and a half-normal prior is chosen for the stratum-specific SD τ_s^2. Rather than explicitly defining the overall PS-MAP prior in terms of the stratum-specific MAP priors, we define the relationship between the stratum-specific means $\theta_{s,1}$, and the overall mean of the current single-arm study θ_1. Then the PS-MAP prior is the distribution induced through this relationship. Specifically, we define

$$\theta_1 = \sum_{s=1}^{S} \frac{n_{s,1}}{N_1} \theta_{s,1}$$

That is, the overall mean of the current study is the weighted sum of the stratum-specific means of the current study.

Reference:

[1] Neuenschwander B, Capkun-Niggli G, Branson M, Spiegelhalter DJ. Summarizing historical information on controls in clinical trials. Clin Trials. 2010;7(1):5-18.

[2] Schmidli H, Gsteiger S, Roychoudhury S, O'Hagan A, Spiegelhalter D, Neuenschwander B. Robust meta-analytic-predictive priors in clinical trials with historical control information. Biometrics 2014; 70(4): 1023-1032.

[3] Zhang H, Shen Y, Li J, Ye H, Chiang AY. Adaptively leveraging external data with robust meta-analytical-predictive prior using empirical Bayes. Pharm Stat. 2023 Sep-Oct;22(5):846-860.

[4] Liu M, Bunn V, Hupf B, Lin J, Lin J. Propensity-score-based meta-analytic predictive prior for incorporating real-world and historical data. Stat Med. 2021 Sep 30;40(22):4794-4808.

Part F The proposed MSDB prior framework combined with EB-rMAP weights, BOX weights and SAM weights

In the proposed MSDB prior framework, the analysis still follows the same steps up to Step 5. The only change is that in Step 4, the robust weight ω_R is calculated using other rMAP-based methods. That is, when constructing the prior under the MSDB approach, we replace the original weight ω_R with one obtained from another method. This allows us to compare the proposed consistency measure with existing methods and demonstrate its advantages. Denote the three comparison methods under this MSDB framework as Box_{MSDB}, EB_{MSDB}, and SAM_{MSDB}.

$$\hat{f}_{MSDB}(\lambda_k|D_{HD}) = (1-\omega_R)\cdot f_{mMAP}(\lambda_k) + \omega_R f_0(\lambda_k)$$
$$= (1-\omega_R)\sum_{j=1}^{J}\omega_j Gamma(a_j, b_j) + \omega_R Gamma(a_0, b_0) \qquad (*)$$

1. SAM_{MSDB}: SAM weights by Self-adapting mixture prior (SAM prior)[1]

SAM prior is an rMAP-based Bayesian method that incorporates a hypothesis testing framework. It uses a likelihood ratio test between current and historical data to compute a robust prior weight. The larger likelihood ratio (i.e., in favor of the null hypothesis), the more information is borrowed.

Step1. Introduce two hypotheses, represented by H_0 and H_1, as follows:

$$H_0: \lambda_k = \lambda_{k,h}, H_1: \lambda_k = \lambda_{k,h} + \delta \ or \ \lambda_k = \lambda_{k,h} - \delta$$

$\lambda_{k,h}$ denotes the hazard rate in the k time interval for the historical data, and δ represents the difference between the historical data and the current trial.

Step2. The extent of information borrowing can be quantified by the likelihood ratio test (LRT) statistic of H_0 and H_1:

$$\mathrm{p} = \frac{p(D|H_0,\lambda_k)}{p(D|H_1,\lambda_k)} = \frac{p(D|\lambda_k = \lambda_{k,h})}{maxp(D|\lambda_k = \lambda_{k,h}+\delta), p(D|\lambda_k = \lambda_{k,h}-\delta)}$$

Where $p(D|\cdot)$ denotes the likelihood. Thus, the robust weights ω_R in MSDB prior $(*)$ can be calculated:

$$\omega_R = \frac{R}{1-R}$$

In practice, $\lambda_{k,h}$ is unknown and can be substituted with an estimate, such as the posterior mean estimate $\widehat{\lambda_{k,h}} = \mathrm{E}(f_{cMAP}(\lambda_k))$ in MSDB prior framework or the maximum likelihood estimate, to calculate ω_R.

2. $\boldsymbol{Box_{MSDB}}$: Box weights by Box's *P* values[2-3]

Box describes how the prior predictive distribution can be used to test the compatibility of a prior and data. This can be used to identify unsuitable priors that conflict with the observed data. The test gives a *P* value that is the probability of predictive distribution of data D_{CTD} being equal of less likely than that of the observed data d_{CTD}, in our setting that is

$$P_{Box}(d_{CTD}) = Pr\{f_{rMAP}(D_{CTD}) \leq f_{rMAP}(d_{CTD})\}$$

Similar to EB-rMAP prior, the robust weights in MSDB prior $(*)$ can be calculated:

$$\omega_{Box} = \begin{Bmatrix} min_{\omega_R}\omega_R{:}P_{Box}(d_{CTD}) \geq \gamma, if \exists \omega_R s.t. P_{Box}(d_{CTD}) \geq \gamma \\ 1 \qquad\qquad\qquad\qquad ,if\ otherwise \end{Bmatrix}$$

3. $\boldsymbol{EB_{MSDB}}$: EB-rMAP weights by EB-rMAP prior[4]

As previously described, we replace the robust weight term in Step 4 of the MSDB prior (specifically in formula (*)) with that derived from the EB-rMAP method. The procedure for computing the EB-rMAP weight has been detailed earlier, and a brief summary is provided below:

$$ppp(d_1) = 2 * min\{Pr_{D_{CTD}|d_{HD}}(T(D_{CTD}) \geq T(d_{CTD})), Pr_{D_{CTD}|d_{HD}}(T(D_{CTD}) \leq T(d_{CTD}))\}$$

$$\omega_{EB} = \begin{Bmatrix} min_{\omega_R}\{\omega_R{:}\, ppp(d_{CTD}) \geq \gamma\}, if \exists \omega_R\ s.t. ppp\,(d_{CTD}) \geq \gamma \\ 1 \qquad\qquad\qquad\qquad ,if\ otherwise \end{Bmatrix}$$

[1] Yang P, Zhao Y, Nie L, Vallejo J, Yuan Y. SAM: Self-adapting mixture prior to dynamically borrow information from historical data in clinical trials. Biometrics. 2023 Dec;79(4):2857-2868.

[2] Box GEP. Sampling and Bayes' Inference in Scientific Modelling and Robustness. Journal of the Royal Statistical Society. Series A (General) 1980; 143(4): 383–480

[3] Gravestock, I., & Held, L. (2017). Adaptive power priors with empirical Bayes for clinical trials. Pharmaceutical Statistics, 16(5), 349–360. doi:10.1002/pst.1814

[4] Zhang H, Shen Y, Li J, Ye H, Chiang AY. Adaptively leveraging external data with robust meta-analytical-predictive prior using empirical Bayes. Pharm Stat. 2023 Sep-Oct;22(5):846-860.

Part G The simulation results show in figure under low baseline imbalance.

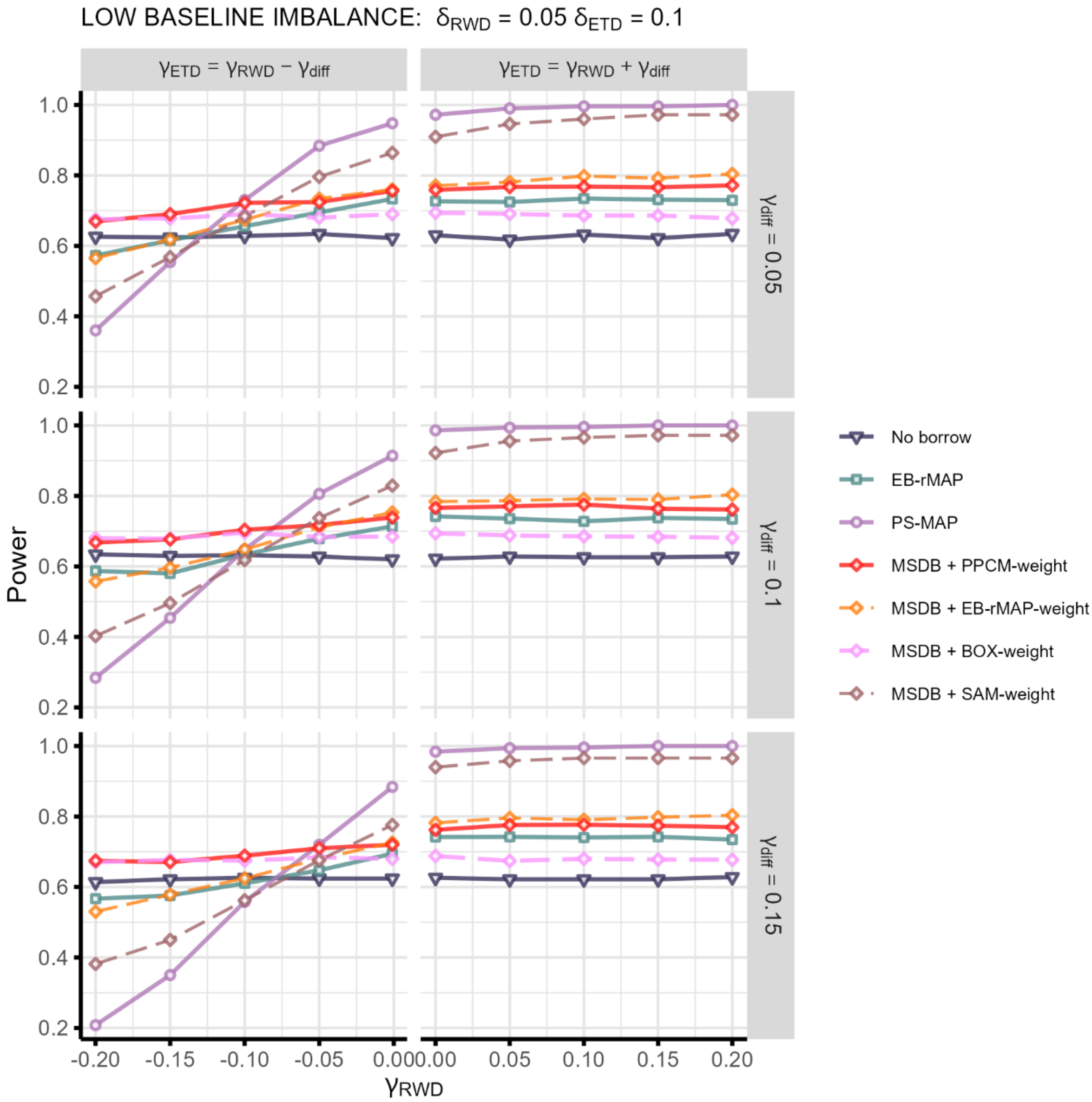

Figure S1. Power of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

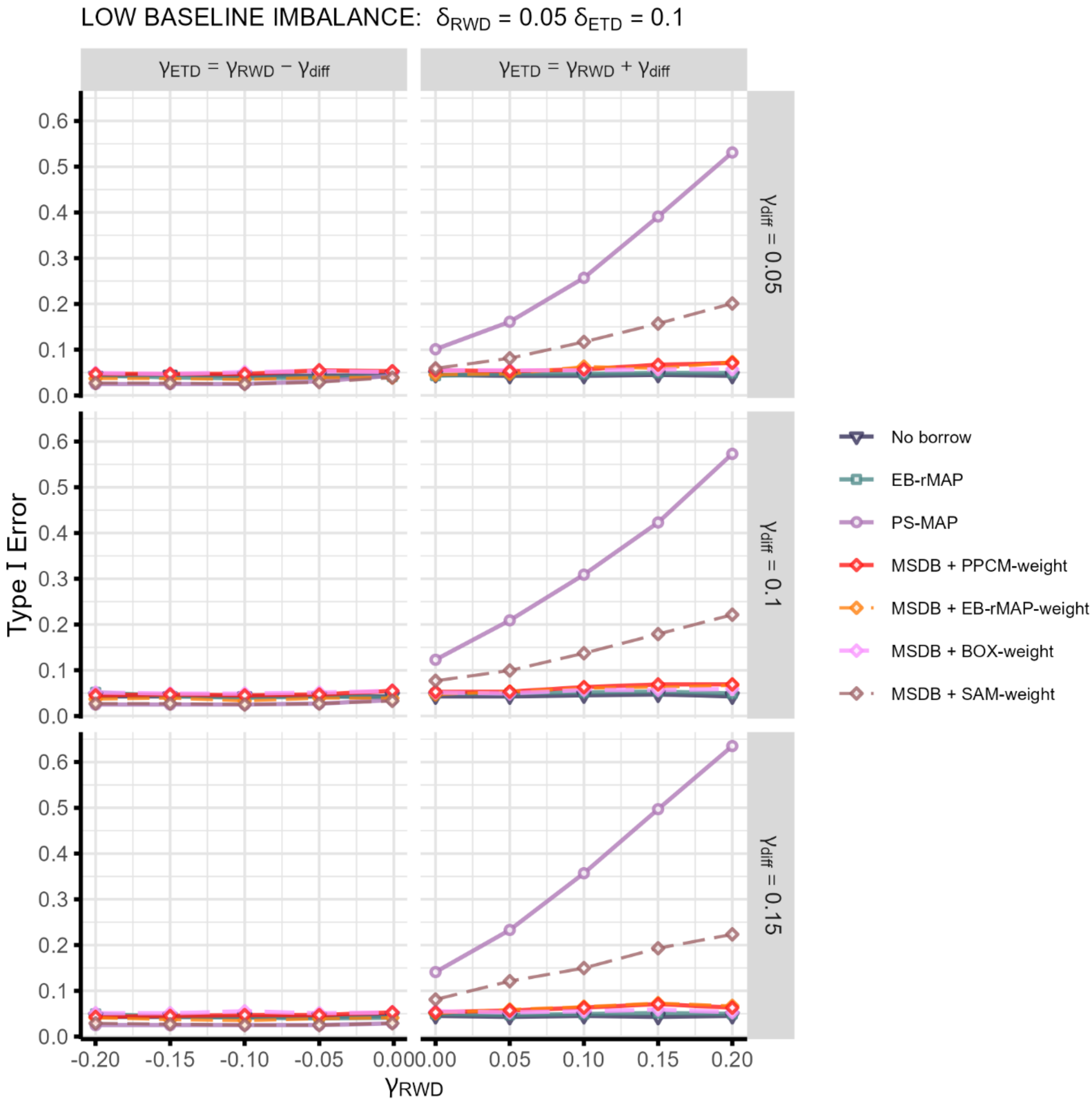

Figure S2. Type I error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

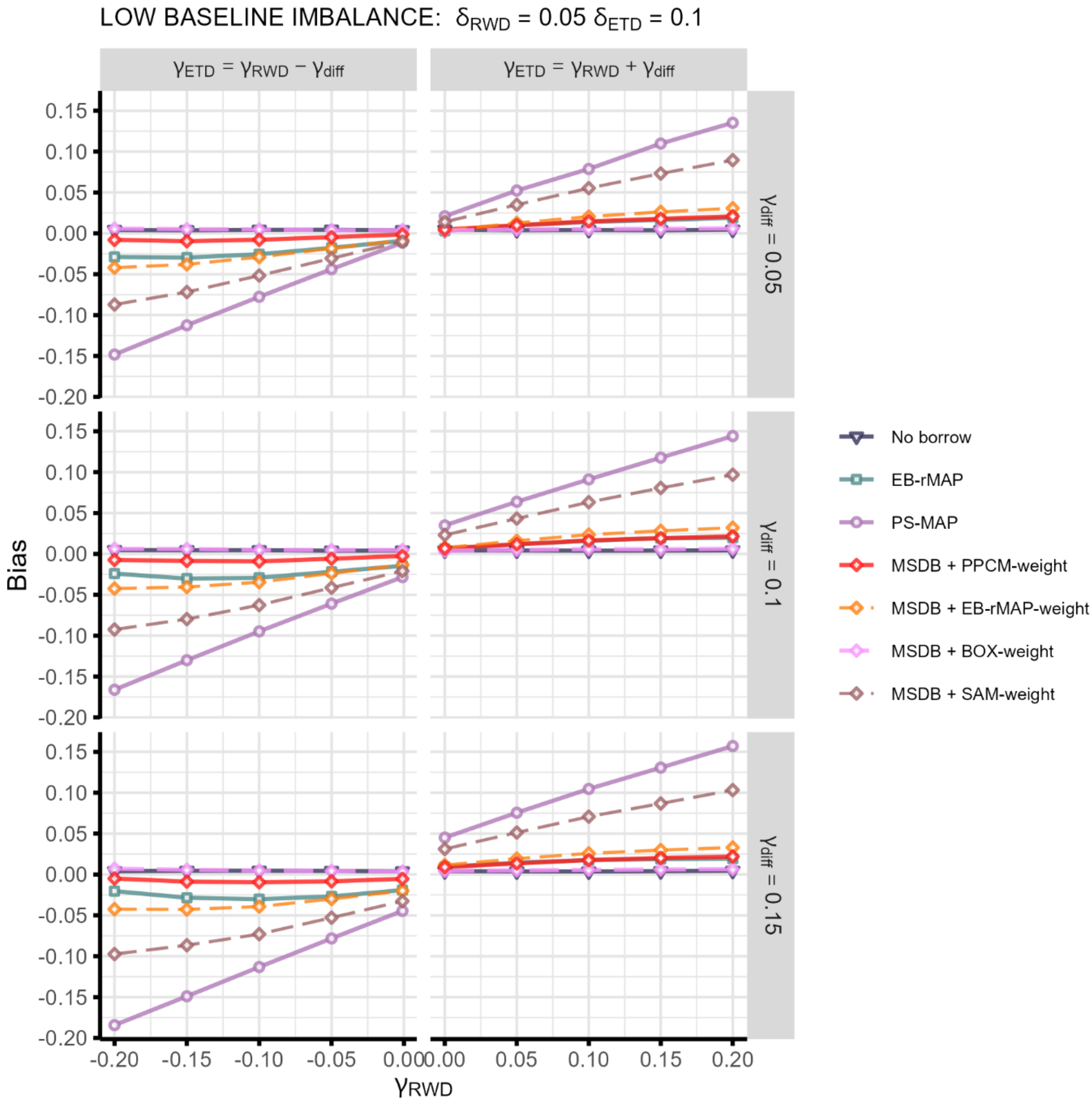

Figure S3. Bias of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

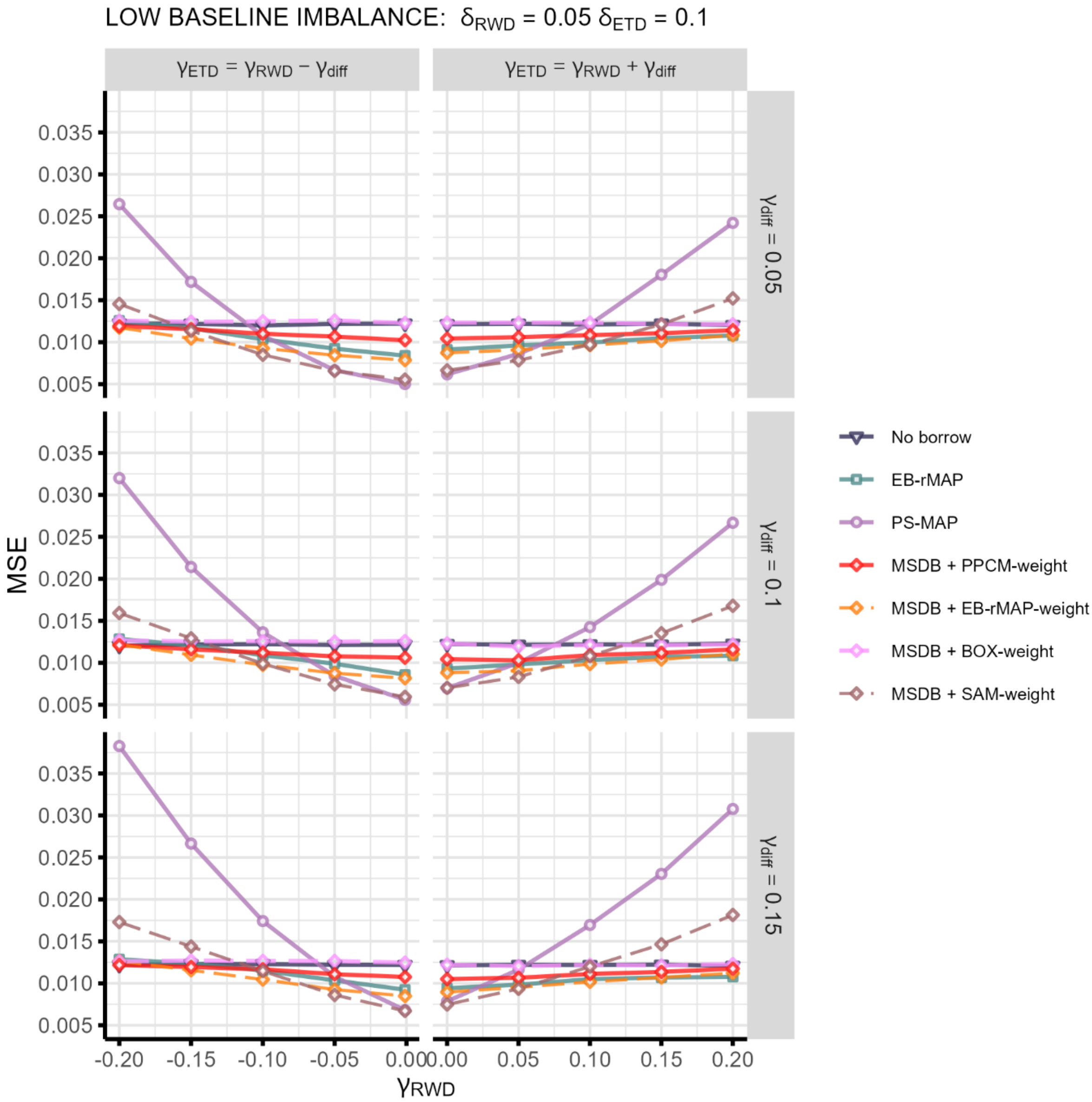

Figure S4. Mean Squared Error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

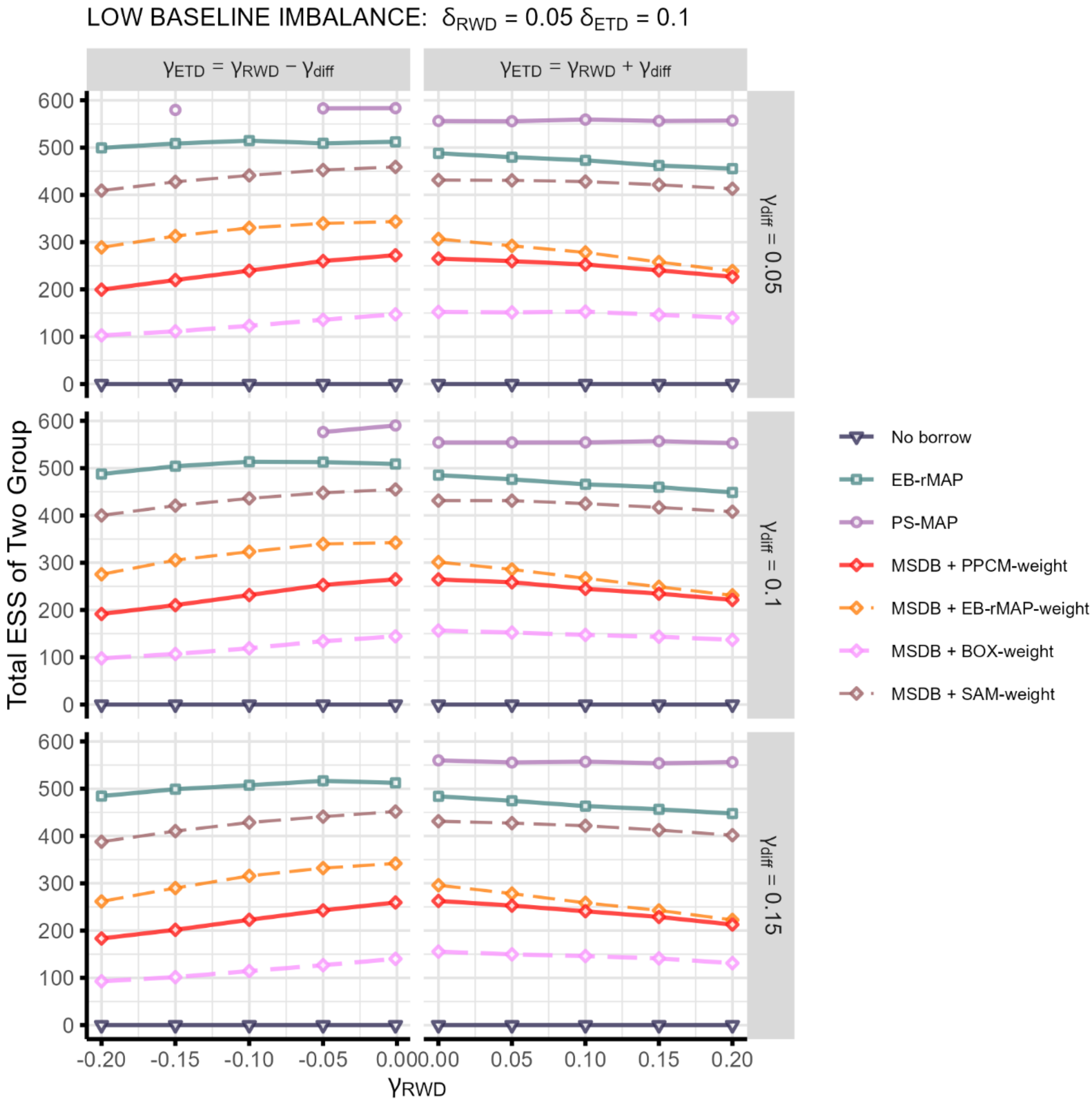

Figure S5. Total effective sample size (ESS) of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

Part H The detailed value of simulation results in all simulation scenarios.

Table S1. Power of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0.634	0.681	0.623	0.396	0.571	0.655	0.476
	-0.15	0.622	0.672	0.583	0.502	0.611	0.658	0.551
	-0.10	0.626	0.693	0.595	0.668	0.651	0.657	0.619
	-0.05	0.634	0.695	0.651	0.770	0.681	0.667	0.699
	-0.00	0.628	0.716	0.682	0.864	0.720	0.680	0.766
	0.00	0.626	0.730	0.663	0.908	0.726	0.673	0.829
	0.05	0.634	0.729	0.682	0.942	0.733	0.664	0.872
	0.10	0.634	0.729	0.670	0.956	0.747	0.659	0.900
	0.15	0.638	0.735	0.681	0.970	0.745	0.665	0.908
	0.20	0.622	0.749	0.665	0.982	0.760	0.665	0.913
0.10	-0.20	0.624	0.671	0.646	0.322	0.575	0.665	0.454
	-0.15	0.622	0.667	0.604	0.452	0.592	0.669	0.518
	-0.10	0.624	0.694	0.580	0.586	0.625	0.663	0.599
	-0.05	0.626	0.692	0.611	0.734	0.669	0.653	0.669
	-0.00	0.632	0.708	0.649	0.840	0.708	0.669	0.742
	0.00	0.624	0.724	0.672	0.918	0.718	0.661	0.844
	0.05	0.630	0.733	0.679	0.946	0.743	0.663	0.880
	0.10	0.624	0.739	0.681	0.966	0.756	0.671	0.902
	0.15	0.624	0.741	0.673	0.980	0.752	0.655	0.915
	0.20	0.622	0.749	0.674	0.986	0.759	0.667	0.920
0.15	-0.20	0.626	0.676	0.653	0.286	0.559	0.666	0.423
	-0.15	0.638	0.678	0.616	0.386	0.575	0.666	0.486
	-0.10	0.626	0.689	0.590	0.516	0.614	0.653	0.568
	-0.05	0.626	0.703	0.587	0.662	0.655	0.663	0.636
	-0.00	0.626	0.702	0.630	0.786	0.698	0.660	0.712
	0.00	0.626	0.736	0.665	0.928	0.738	0.667	0.856
	0.05	0.638	0.729	0.659	0.956	0.737	0.660	0.887
	0.10	0.626	0.754	0.682	0.968	0.749	0.669	0.903
	0.15	0.626	0.746	0.669	0.978	0.766	0.667	0.923
	0.20	0.628	0.744	0.675	0.986	0.757	0.668	0.930

Note: power values were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S2. Type I error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0.043	0.051	0.073	0.025	0.039	0.053	0.029
0.05	-0.15	0.045	0.049	0.069	0.025	0.037	0.051	0.029
0.05	-0.10	0.045	0.051	0.056	0.025	0.037	0.057	0.029
0.05	-0.05	0.043	0.049	0.055	0.027	0.043	0.051	0.031
0.05	-0.00	0.043	0.057	0.054	0.039	0.045	0.055	0.039
0.05	0.00	0.045	0.051	0.051	0.069	0.045	0.051	0.043
0.05	0.05	0.043	0.049	0.049	0.105	0.047	0.049	0.065
0.05	0.10	0.045	0.049	0.047	0.145	0.049	0.047	0.079
0.05	0.15	0.047	0.051	0.046	0.187	0.051	0.049	0.095
0.05	0.20	0.043	0.061	0.048	0.269	0.061	0.051	0.13
0.10	-0.20	0.043	0.053	0.087	0.025	0.041	0.051	0.029
0.10	-0.15	0.043	0.049	0.071	0.025	0.039	0.053	0.029
0.10	-0.10	0.043	0.051	0.064	0.025	0.037	0.051	0.029
0.10	-0.05	0.045	0.055	0.057	0.025	0.041	0.055	0.031
0.10	-0.00	0.043	0.049	0.051	0.031	0.043	0.055	0.037
0.10	0.00	0.047	0.049	0.051	0.085	0.047	0.045	0.051
0.10	0.05	0.043	0.051	0.051	0.115	0.047	0.051	0.067
0.10	0.10	0.043	0.053	0.046	0.169	0.051	0.049	0.085
0.10	0.15	0.043	0.055	0.046	0.229	0.055	0.047	0.112
0.10	0.20	0.045	0.055	0.048	0.293	0.059	0.049	0.127
0.15	-0.20	0.045	0.053	0.09	0.025	0.043	0.053	0.029
0.15	-0.15	0.043	0.049	0.073	0.025	0.037	0.053	0.029
0.15	-0.10	0.047	0.051	0.069	0.025	0.037	0.055	0.029
0.15	-0.05	0.045	0.053	0.055	0.025	0.035	0.053	0.029
0.15	-0.00	0.047	0.051	0.055	0.029	0.043	0.055	0.033
0.15	0.00	0.045	0.051	0.045	0.099	0.049	0.051	0.049
0.15	0.05	0.045	0.049	0.048	0.141	0.045	0.047	0.074
0.15	0.10	0.045	0.051	0.05	0.185	0.055	0.051	0.092
0.15	0.15	0.045	0.059	0.052	0.263	0.055	0.051	0.122
0.15	0.20	0.045	0.051	0.05	0.313	0.053	0.049	0.146

Note: type I error were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S3. Bias of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0.468	-0.194	0.525	-12.647	-2.941	0.585	-6.974
0.05	-0.15	0.412	-0.356	-0.709	-9.522	-2.669	0.512	-5.726
0.05	-0.10	0.400	-0.364	-1.197	-6.449	-2.114	0.480	-4.224
0.05	-0.05	0.444	-0.205	-1.085	-3.713	-1.349	0.373	-2.498
0.05	-0.00	0.416	0.118	-0.735	-1.138	-0.509	0.456	-0.852
0.05	0.00	0.387	0.362	0.245	1.426	0.162	0.440	0.771
0.05	0.05	0.412	0.774	0.681	3.657	0.865	0.465	2.402
0.05	0.10	0.440	1.116	0.964	5.650	1.400	0.446	3.793
0.05	0.15	0.430	1.504	1.035	7.860	1.908	0.559	5.192
0.05	0.20	0.424	1.705	0.999	9.804	2.243	0.549	6.444
0.10	-0.20	0.424	-0.034	1.295	-14.071	-2.934	0.629	-7.414
0.10	-0.15	0.431	-0.275	0.091	-10.986	-2.828	0.596	-6.320
0.10	-0.10	0.401	-0.396	-1.034	-7.935	-2.386	0.538	-4.915
0.10	-0.05	0.399	-0.404	-1.372	-5.000	-1.778	0.334	-3.318
0.10	-0.00	0.459	-0.025	-1.017	-2.326	-0.896	0.423	-1.588
0.10	0.00	0.489	0.550	0.498	2.204	0.496	0.450	1.452
0.10	0.05	0.435	0.916	0.786	4.628	1.090	0.418	2.915
0.10	0.10	0.397	1.224	0.921	6.773	1.568	0.448	4.357
0.10	0.15	0.420	1.555	1.099	8.797	2.023	0.526	5.712
0.10	0.20	0.380	1.813	1.143	10.647	2.344	0.631	6.955
0.15	-0.20	0.407	0.010	1.718	-15.669	-3.012	0.636	-7.913
0.15	-0.15	0.437	-0.327	0.537	-12.506	-2.992	0.560	-6.895
0.15	-0.10	0.397	-0.453	-0.529	-9.426	-2.711	0.466	-5.633
0.15	-0.05	0.371	-0.371	-1.151	-6.389	-2.054	0.476	-4.059
0.15	-0.00	0.406	-0.254	-1.418	-3.593	-1.376	0.426	-2.469
0.15	0.00	0.392	0.779	0.558	3.368	0.850	0.523	2.130
0.15	0.05	0.436	1.046	0.749	5.637	1.298	0.405	3.469
0.15	0.10	0.399	1.404	1.102	7.421	1.746	0.546	4.829
0.15	0.15	0.400	1.759	1.145	9.471	2.244	0.638	6.293
0.15	0.20	0.425	1.850	1.074	11.502	2.439	0.613	7.393

Note: Bias was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method

Table S4. Mean Squared Error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	1.219	1.250	1.542	2.208	1.149	1.257	1.311
0.05	-0.15	1.218	1.221	1.489	1.523	1.075	1.264	1.108
0.05	-0.10	1.219	1.170	1.387	1.049	0.982	1.257	0.916
0.05	-0.05	1.217	1.153	1.271	0.788	0.945	1.257	0.811
0.05	-0.00	1.215	1.129	1.163	0.682	0.915	1.242	0.763
0.05	0.00	1.220	1.056	1.156	0.744	0.935	1.242	0.780
0.05	0.05	1.207	1.080	1.147	0.886	0.968	1.222	0.851
0.05	0.10	1.207	1.089	1.185	1.087	0.995	1.210	0.965
0.05	0.15	1.212	1.096	1.184	1.403	1.026	1.205	1.104
0.05	0.20	1.226	1.150	1.197	1.766	1.082	1.232	1.299
0.10	-0.20	1.225	1.251	1.618	2.571	1.184	1.262	1.412
0.10	-0.15	1.226	1.235	1.508	1.825	1.101	1.247	1.186
0.10	-0.10	1.217	1.208	1.409	1.251	1.032	1.275	1.005
0.10	-0.05	1.215	1.158	1.345	0.895	0.965	1.256	0.856
0.10	-0.00	1.219	1.152	1.223	0.715	0.931	1.253	0.776
0.10	0.00	1.221	1.075	1.162	0.789	0.950	1.246	0.811
0.10	0.05	1.216	1.069	1.182	0.980	0.975	1.222	0.883
0.10	0.10	1.220	1.091	1.194	1.231	1.004	1.218	1.010
0.10	0.15	1.226	1.134	1.209	1.575	1.055	1.233	1.182
0.10	0.20	1.218	1.137	1.212	1.948	1.077	1.205	1.353
0.15	-0.20	1.218	1.265	1.658	3.033	1.225	1.267	1.518
0.15	-0.15	1.202	1.239	1.547	2.168	1.137	1.246	1.287
0.15	-0.10	1.218	1.233	1.448	1.511	1.070	1.269	1.089
0.15	-0.05	1.220	1.178	1.402	1.039	0.990	1.270	0.923
0.15	-0.00	1.216	1.140	1.282	0.776	0.937	1.250	0.800
0.15	0.00	1.218	1.076	1.172	0.869	0.966	1.234	0.843
0.15	0.05	1.210	1.085	1.195	1.079	0.987	1.213	0.926
0.15	0.10	1.215	1.116	1.195	1.322	1.031	1.220	1.068
0.15	0.15	1.219	1.135	1.213	1.700	1.058	1.218	1.250
0.15	0.20	1.211	1.158	1.213	2.139	1.089	1.218	1.437

Note: MSE was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S5. Borrowed effective Sample Size of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0	133	454	466	161	59	237
0.05	-0.15	0	143	473	453	173	61	244
0.05	-0.10	0	155	485	443	183	68	250
0.05	-0.05	0	161	495	435	185	73	251
0.05	-0.00	0	166	499	425	185	77	252
0.05	0.00	0	166	451	384	166	82	233
0.05	0.05	0	164	446	382	162	84	232
0.05	0.10	0	159	431	378	154	82	228
0.05	0.15	0	154	423	378	144	81	224
0.05	0.20	0	144	418	375	134	74	218
0.10	-0.20	0	127	445	465	154	54	233
0.10	-0.15	0	138	464	457	167	58	241
0.10	-0.10	0	150	480	448	179	67	247
0.10	-0.05	0	159	489	439	185	71	252
0.10	-0.00	0	164	493	429	186	74	251
0.10	0.00	0	165	445	382	164	81	233
0.10	0.05	0	162	436	380	159	83	230
0.10	0.10	0	157	429	377	151	83	226
0.10	0.15	0	149	422	375	140	77	221
0.10	0.20	0	141	416	373	130	73	215
0.15	-0.20	0	121	437	471	147	51	227
0.15	-0.15	0	133	452	461	162	57	237
0.15	-0.10	0	145	468	454	174	63	245
0.15	-0.05	0	155	487	446	183	68	249
0.15	-0.00	0	162	494	434	186	73	253
0.15	0.00	0	165	440	380	162	83	232
0.15	0.05	0	161	430	378	155	82	229
0.15	0.10	0	155	425	378	147	80	224
0.15	0.15	0	145	418	373	136	75	219
0.15	0.20	0	136	413	372	126	71	213

Note: The effective sample size (ESS) was rounded down to the nearest integer; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S6. Power of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0.626	0.669	0.573	0.360	0.565	0.675	0.457
0.05	-0.15	0.624	0.690	0.616	0.554	0.618	0.678	0.568
0.05	-0.10	0.628	0.722	0.656	0.730	0.674	0.690	0.684
0.05	-0.05	0.634	0.724	0.695	0.884	0.734	0.680	0.796
0.05	-0.00	0.622	0.756	0.733	0.948	0.760	0.690	0.864
0.05	0.00	0.630	0.759	0.727	0.972	0.771	0.694	0.909
0.05	0.05	0.618	0.767	0.724	0.990	0.781	0.691	0.946
0.05	0.10	0.632	0.768	0.734	0.996	0.798	0.686	0.960
0.05	0.15	0.622	0.766	0.731	0.996	0.792	0.686	0.972
0.05	0.20	0.634	0.772	0.729	1.000	0.804	0.678	0.972
0.10	-0.20	0.634	0.668	0.587	0.284	0.557	0.680	0.402
0.10	-0.15	0.630	0.677	0.580	0.454	0.596	0.679	0.496
0.10	-0.10	0.632	0.704	0.634	0.648	0.648	0.696	0.618
0.10	-0.05	0.628	0.717	0.679	0.806	0.711	0.683	0.737
0.10	-0.00	0.620	0.739	0.713	0.914	0.753	0.685	0.829
0.10	0.00	0.622	0.766	0.742	0.986	0.784	0.694	0.922
0.10	0.05	0.628	0.771	0.736	0.994	0.787	0.688	0.956
0.10	0.10	0.626	0.776	0.728	0.996	0.792	0.685	0.966
0.10	0.15	0.626	0.764	0.738	1.000	0.790	0.684	0.972
0.10	0.20	0.628	0.762	0.734	1.000	0.804	0.681	0.972
0.15	-0.20	0.614	0.675	0.567	0.208	0.530	0.671	0.382
0.15	-0.15	0.622	0.671	0.576	0.350	0.578	0.677	0.450
0.15	-0.10	0.626	0.689	0.610	0.558	0.624	0.675	0.562
0.15	-0.05	0.624	0.710	0.647	0.720	0.680	0.684	0.676
0.15	-0.00	0.624	0.720	0.695	0.884	0.726	0.680	0.776
0.15	0.00	0.626	0.762	0.742	0.984	0.782	0.688	0.940
0.15	0.05	0.622	0.776	0.742	0.994	0.796	0.674	0.958
0.15	0.10	0.622	0.777	0.740	0.996	0.791	0.680	0.966
0.15	0.15	0.622	0.774	0.742	1.000	0.798	0.678	0.966
0.15	0.20	0.628	0.770	0.735	1.000	0.804	0.677	0.966

Note: power values were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S7. Type I errorof the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0.043	0.047	0.043	0.025	0.037	0.049	0.027
0.05	-0.15	0.045	0.047	0.039	0.025	0.037	0.047	0.027
0.05	-0.10	0.043	0.047	0.037	0.025	0.035	0.051	0.025
0.05	-0.05	0.043	0.055	0.039	0.031	0.039	0.053	0.029
0.05	-0.00	0.045	0.053	0.041	0.043	0.039	0.051	0.039
0.05	0.00	0.045	0.055	0.043	0.101	0.045	0.055	0.059
0.05	0.05	0.043	0.053	0.047	0.161	0.047	0.055	0.081
0.05	0.10	0.043	0.057	0.047	0.257	0.063	0.055	0.117
0.05	0.15	0.045	0.067	0.049	0.391	0.059	0.057	0.157
0.05	0.20	0.043	0.071	0.049	0.531	0.073	0.057	0.201
0.10	-0.20	0.043	0.045	0.052	0.025	0.037	0.051	0.027
0.10	-0.15	0.043	0.047	0.044	0.025	0.039	0.049	0.027
0.10	-0.10	0.043	0.045	0.039	0.025	0.033	0.049	0.025
0.10	-0.05	0.043	0.047	0.043	0.027	0.039	0.051	0.027
0.10	-0.00	0.043	0.055	0.039	0.035	0.039	0.055	0.033
0.10	0.00	0.043	0.053	0.049	0.123	0.047	0.051	0.077
0.10	0.05	0.043	0.053	0.049	0.209	0.053	0.049	0.099
0.10	0.10	0.045	0.063	0.052	0.309	0.061	0.057	0.137
0.10	0.15	0.047	0.069	0.053	0.423	0.063	0.057	0.179
0.10	0.20	0.043	0.069	0.049	0.573	0.067	0.059	0.221
0.15	-0.20	0.043	0.043	0.05	0.025	0.041	0.051	0.029
0.15	-0.15	0.043	0.045	0.043	0.025	0.037	0.051	0.027
0.15	-0.10	0.043	0.047	0.041	0.025	0.035	0.055	0.025
0.15	-0.05	0.043	0.047	0.039	0.025	0.039	0.051	0.025
0.15	-0.00	0.045	0.053	0.041	0.029	0.041	0.053	0.029
0.15	0.00	0.045	0.053	0.049	0.141	0.051	0.055	0.081
0.15	0.05	0.043	0.057	0.047	0.233	0.059	0.053	0.121
0.15	0.10	0.045	0.063	0.049	0.357	0.065	0.055	0.15
0.15	0.15	0.043	0.071	0.051	0.497	0.073	0.059	0.193
0.15	0.20	0.045	0.063	0.049	0.635	0.067	0.053	0.223

Note: type I error were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S8. Bias of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0.411	-0.803	-2.885	-14.820	-4.200	0.583	-8.709
0.05	-0.15	0.384	-0.957	-2.960	-11.243	-3.795	0.512	-7.180
0.05	-0.10	0.431	-0.784	-2.554	-7.763	-2.897	0.476	-5.162
0.05	-0.05	0.440	-0.465	-1.776	-4.379	-1.836	0.395	-3.062
0.05	-0.00	0.381	-0.136	-0.908	-1.138	-0.834	0.393	-0.993
0.05	0.00	0.444	0.467	0.305	2.091	0.357	0.370	1.403
0.05	0.05	0.390	0.984	0.979	5.236	1.257	0.468	3.496
0.05	0.10	0.414	1.465	1.396	7.876	2.042	0.527	5.525
0.05	0.15	0.381	1.783	1.636	10.980	2.624	0.559	7.317
0.05	0.20	0.449	2.080	1.887	13.527	3.065	0.622	8.950
0.10	-0.20	0.462	-0.735	-2.410	-16.616	-4.238	0.633	-9.245
0.10	-0.15	0.447	-0.856	-3.017	-13.004	-4.052	0.613	-7.974
0.10	-0.10	0.446	-0.914	-2.919	-9.474	-3.456	0.480	-6.260
0.10	-0.05	0.391	-0.590	-2.185	-6.082	-2.373	0.478	-4.138
0.10	-0.00	0.403	-0.252	-1.450	-2.839	-1.347	0.472	-2.095
0.10	0.00	0.421	0.670	0.622	3.488	0.753	0.385	2.311
0.10	0.05	0.416	1.175	1.172	6.377	1.603	0.490	4.321
0.10	0.10	0.394	1.646	1.609	9.114	2.353	0.597	6.325
0.10	0.15	0.406	1.928	1.926	11.774	2.821	0.574	8.064
0.10	0.20	0.424	2.148	1.985	14.410	3.203	0.648	9.682
0.15	-0.20	0.393	-0.498	-2.033	-18.426	-4.246	0.700	-9.735
0.15	-0.15	0.447	-0.874	-2.847	-14.892	-4.277	0.582	-8.656
0.15	-0.10	0.455	-0.954	-3.020	-11.316	-3.921	0.486	-7.293
0.15	-0.05	0.429	-0.836	-2.688	-7.822	-3.002	0.440	-5.288
0.15	-0.00	0.377	-0.538	-1.911	-4.452	-1.996	0.351	-3.260
0.15	0.00	0.399	0.906	0.937	4.507	1.144	0.442	3.115
0.15	0.05	0.372	1.355	1.442	7.554	1.935	0.505	5.127
0.15	0.10	0.364	1.765	1.760	10.463	2.576	0.573	7.072
0.15	0.15	0.397	2.014	1.893	13.066	2.983	0.616	8.677
0.15	0.20	0.452	2.202	1.930	15.708	3.296	0.652	10.323

Note: Bias was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S9. Mean Squared Error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	1.223	1.191	1.258	2.645	1.174	1.255	1.456
0.05	-0.15	1.220	1.156	1.166	1.719	1.043	1.244	1.135
0.05	-0.10	1.199	1.100	1.035	1.078	0.927	1.249	0.850
0.05	-0.05	1.219	1.067	0.923	0.665	0.845	1.258	0.658
0.05	-0.00	1.221	1.024	0.840	0.502	0.786	1.229	0.554
0.05	0.00	1.215	1.042	0.912	0.617	0.873	1.233	0.664
0.05	0.05	1.220	1.060	0.962	0.861	0.909	1.232	0.784
0.05	0.10	1.211	1.084	0.996	1.212	0.965	1.233	0.970
0.05	0.15	1.221	1.107	1.047	1.804	1.017	1.215	1.213
0.05	0.20	1.204	1.143	1.080	2.422	1.082	1.214	1.521
0.10	-0.20	1.203	1.210	1.284	3.200	1.216	1.267	1.592
0.10	-0.15	1.218	1.160	1.209	2.141	1.094	1.254	1.291
0.10	-0.10	1.221	1.120	1.090	1.362	0.975	1.256	0.988
0.10	-0.05	1.213	1.077	0.989	0.845	0.876	1.250	0.742
0.10	-0.00	1.215	1.060	0.857	0.559	0.816	1.258	0.594
0.10	0.00	1.222	1.042	0.930	0.697	0.881	1.230	0.701
0.10	0.05	1.215	1.029	0.980	0.998	0.905	1.193	0.831
0.10	0.10	1.219	1.091	1.031	1.425	0.985	1.212	1.079
0.10	0.15	1.216	1.118	1.072	1.988	1.040	1.210	1.351
0.10	0.20	1.226	1.158	1.084	2.668	1.104	1.219	1.678
0.15	-0.20	1.219	1.218	1.286	3.827	1.263	1.262	1.730
0.15	-0.15	1.230	1.195	1.236	2.665	1.157	1.271	1.438
0.15	-0.10	1.228	1.167	1.150	1.741	1.045	1.266	1.146
0.15	-0.05	1.220	1.109	1.035	1.080	0.926	1.266	0.861
0.15	-0.00	1.219	1.076	0.924	0.680	0.849	1.246	0.671
0.15	0.00	1.214	1.051	0.942	0.785	0.895	1.221	0.747
0.15	0.05	1.219	1.066	0.984	1.163	0.953	1.207	0.934
0.15	0.10	1.218	1.111	1.050	1.695	1.018	1.219	1.200
0.15	0.15	1.222	1.136	1.069	2.304	1.070	1.214	1.464
0.15	0.20	1.208	1.174	1.078	3.077	1.122	1.229	1.814

Note: MSE was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S10. Total effective Sample Size of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance with other methods as reference.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$	*EB-rMAP*	*PS-MAP*	EBW_{MSDB}	BOX_{MSDB}	SAM_{MSDB}
0.05	-0.20	0	199	499	—	288	102	409
0.05	-0.15	0	219	508	579	312	111	427
0.05	-0.10	0	239	514	—	330	123	441
0.05	-0.05	0	260	508	582	339	135	452
0.05	-0.00	0	272	512	583	343	147	459
0.05	0.00	0	265	487	556	306	152	431
0.05	0.05	0	259	479	555	292	151	430
0.05	0.10	0	252	473	559	278	152	428
0.05	0.15	0	240	462	556	257	146	421
0.05	0.20	0	226	455	557	238	140	412
0.10	-0.20	0	191	487	—	275	97	400
0.10	-0.15	0	210	504	—	305	106	420
0.10	-0.10	0	231	513	—	323	119	436
0.10	-0.05	0	252	512	576	339	133	447
0.10	-0.00	0	264	508	590	342	144	454
0.10	0.00	0	264	485	554	301	156	431
0.10	0.05	0	258	476	554	285	152	431
0.10	0.10	0	244	465	554	267	147	425
0.10	0.15	0	234	459	557	249	143	416
0.10	0.20	0	221	448	552	230	136	407
0.15	-0.20	0	183	484	—	261	92	387
0.15	-0.15	0	201	499	—	289	101	410
0.15	-0.10	0	222	507	—	315	114	428
0.15	-0.05	0	242	516	—	332	126	440
0.15	-0.00	0	259	512	—	341	140	451
0.15	0.00	0	262	483	559	295	155	431
0.15	0.05	0	252	474	555	278	149	427
0.15	0.10	0	240	463	557	258	146	421
0.15	0.15	0	228	456	553	242	141	412
0.15	0.20	0	212	447	556	222	131	401

Note: The effective sample size (ESS) was rounded down to the nearest integer; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method.

Table S11. Power of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0.634	0.627	0.649	0.663	0.681	0.675
-0.15	0.05	0.622	0.652	0.662	0.666	0.672	0.680
-0.10	0.05	0.626	0.687	0.697	0.683	0.693	0.679
-0.05	0.05	0.634	0.715	0.717	0.709	0.695	0.685
-0.00	0.05	0.628	0.754	0.740	0.738	0.716	0.706
0.00	0.05	0.626	0.792	0.764	0.744	0.730	0.690
0.05	0.05	0.634	0.806	0.789	0.749	0.729	0.702
0.10	0.05	0.634	0.808	0.788	0.766	0.729	0.705
0.15	0.05	0.638	0.814	0.800	0.772	0.735	0.705
0.20	0.05	0.622	0.812	0.796	0.778	0.749	0.713
-0.20	0.10	0.624	0.607	0.643	0.663	0.671	0.675
-0.15	0.10	0.622	0.635	0.657	0.661	0.667	0.677
-0.10	0.10	0.624	0.669	0.692	0.696	0.694	0.683
-0.05	0.10	0.626	0.692	0.698	0.690	0.692	0.677
-0.00	0.10	0.632	0.744	0.736	0.728	0.708	0.690
0.00	0.10	0.624	0.791	0.771	0.748	0.724	0.694
0.05	0.10	0.630	0.822	0.788	0.762	0.733	0.705
0.10	0.10	0.624	0.818	0.792	0.776	0.739	0.701
0.15	0.10	0.624	0.810	0.790	0.772	0.741	0.703
0.20	0.10	0.622	0.817	0.799	0.771	0.749	0.709
-0.20	0.15	0.626	0.585	0.636	0.664	0.676	0.672
-0.15	0.15	0.638	0.623	0.654	0.666	0.678	0.672
-0.10	0.15	0.626	0.661	0.671	0.681	0.689	0.685
-0.05	0.15	0.626	0.691	0.699	0.701	0.703	0.689
-0.00	0.15	0.626	0.728	0.722	0.716	0.702	0.684
0.00	0.15	0.626	0.807	0.787	0.761	0.736	0.714
0.05	0.15	0.638	0.812	0.794	0.759	0.729	0.700
0.10	0.15	0.626	0.812	0.790	0.770	0.754	0.707
0.15	0.15	0.626	0.810	0.788	0.774	0.746	0.708
0.20	0.15	0.628	0.819	0.791	0.767	0.744	0.706

Note: power values were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights;

Table S12. Type I error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0.043	0.037	0.039	0.055	0.051	0.053
-0.15	0.05	0.045	0.039	0.047	0.051	0.049	0.051
-0.10	0.05	0.045	0.039	0.047	0.051	0.051	0.053
-0.05	0.05	0.043	0.047	0.051	0.049	0.049	0.053
-0.00	0.05	0.043	0.053	0.057	0.059	0.057	0.049
0.00	0.05	0.045	0.051	0.055	0.053	0.051	0.047
0.05	0.05	0.043	0.061	0.055	0.053	0.049	0.047
0.10	0.05	0.045	0.067	0.063	0.055	0.049	0.047
0.15	0.05	0.047	0.079	0.077	0.065	0.051	0.051
0.20	0.05	0.043	0.092	0.084	0.076	0.061	0.057
-0.20	0.10	0.043	0.037	0.043	0.051	0.053	0.053
-0.15	0.10	0.043	0.041	0.049	0.051	0.049	0.051
-0.10	0.10	0.043	0.041	0.047	0.051	0.051	0.049
-0.05	0.10	0.045	0.043	0.051	0.053	0.055	0.049
-0.00	0.10	0.043	0.047	0.053	0.053	0.049	0.051
0.00	0.10	0.047	0.053	0.051	0.049	0.049	0.049
0.05	0.10	0.043	0.061	0.059	0.053	0.051	0.047
0.10	0.10	0.043	0.073	0.065	0.057	0.053	0.049
0.15	0.10	0.043	0.082	0.076	0.071	0.055	0.049
0.20	0.10	0.045	0.087	0.085	0.071	0.055	0.051
-0.20	0.15	0.045	0.033	0.047	0.053	0.053	0.051
-0.15	0.15	0.043	0.039	0.043	0.051	0.049	0.051
-0.10	0.15	0.047	0.047	0.045	0.051	0.051	0.051
-0.05	0.15	0.045	0.035	0.047	0.051	0.053	0.049
-0.00	0.15	0.047	0.045	0.049	0.051	0.051	0.051
0.00	0.15	0.045	0.051	0.053	0.049	0.051	0.047
0.05	0.15	0.045	0.065	0.057	0.055	0.049	0.047
0.10	0.15	0.045	0.073	0.069	0.061	0.051	0.051
0.15	0.15	0.045	0.085	0.073	0.061	0.059	0.053
0.20	0.15	0.045	0.089	0.081	0.071	0.051	0.047

Note: type I error were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S13. Bias of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0.468	-2.986	-1.758	-0.843	-0.194	0.277
-0.15	0.05	0.412	-2.574	-1.723	-0.955	-0.356	0.048
-0.10	0.05	0.400	-2.122	-1.381	-0.867	-0.364	-0.035
-0.05	0.05	0.444	-1.269	-0.834	-0.455	-0.205	0.040
-0.00	0.05	0.416	-0.324	-0.176	-0.026	0.118	0.257
0.00	0.05	0.387	0.573	0.503	0.447	0.362	0.292
0.05	0.05	0.412	1.533	1.305	1.051	0.774	0.558
0.10	0.05	0.440	2.154	1.840	1.452	1.116	0.785
0.15	0.05	0.430	2.866	2.414	1.945	1.504	1.091
0.20	0.05	0.424	3.272	2.784	2.255	1.705	1.282
-0.20	0.10	0.424	-3.066	-1.664	-0.648	-0.034	0.433
-0.15	0.10	0.431	-2.836	-1.725	-0.956	-0.275	0.181
-0.10	0.10	0.401	-2.461	-1.566	-0.925	-0.396	0.054
-0.05	0.10	0.399	-1.739	-1.162	-0.731	-0.404	-0.126
-0.00	0.10	0.459	-0.741	-0.466	-0.279	-0.025	0.144
0.00	0.10	0.489	0.976	0.885	0.699	0.550	0.417
0.05	0.10	0.435	1.741	1.535	1.207	0.916	0.650
0.10	0.10	0.397	2.391	2.018	1.616	1.224	0.903
0.15	0.10	0.420	3.018	2.561	2.035	1.555	1.139
0.20	0.10	0.380	3.424	2.891	2.362	1.813	1.366
-0.20	0.15	0.407	-3.146	-1.617	-0.628	0.010	0.467
-0.15	0.15	0.437	-3.048	-1.775	-0.948	-0.327	0.188
-0.10	0.15	0.397	-2.749	-1.741	-1.092	-0.453	-0.013
-0.05	0.15	0.371	-2.058	-1.270	-0.786	-0.371	-0.005
-0.00	0.15	0.406	-1.310	-0.879	-0.571	-0.254	-0.017
0.00	0.15	0.392	1.334	1.226	0.993	0.779	0.605
0.05	0.15	0.436	2.047	1.793	1.419	1.046	0.736
0.10	0.15	0.399	2.602	2.242	1.797	1.404	1.019
0.15	0.15	0.400	3.256	2.785	2.255	1.759	1.312
0.20	0.15	0.425	3.539	2.957	2.396	1.850	1.406

Note: Bias was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S14. Mean Squared Error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	1.219	1.167	1.226	1.238	1.250	1.272
-0.15	0.05	1.218	1.105	1.153	1.195	1.221	1.241
-0.10	0.05	1.219	1.002	1.088	1.130	1.170	1.210
-0.05	0.05	1.217	0.960	1.036	1.113	1.153	1.187
-0.00	0.05	1.215	0.923	1.001	1.085	1.129	1.161
0.00	0.05	1.220	0.943	0.980	1.019	1.056	1.105
0.05	0.05	1.207	0.984	1.003	1.041	1.080	1.113
0.10	0.05	1.207	1.044	1.046	1.061	1.089	1.105
0.15	0.05	1.212	1.099	1.084	1.092	1.096	1.116
0.20	0.05	1.226	1.189	1.161	1.153	1.150	1.157
-0.20	0.10	1.225	1.197	1.217	1.260	1.251	1.256
-0.15	0.10	1.226	1.135	1.167	1.199	1.235	1.242
-0.10	0.10	1.217	1.060	1.134	1.179	1.208	1.232
-0.05	0.10	1.215	0.983	1.046	1.123	1.158	1.190
-0.00	0.10	1.219	0.946	1.030	1.090	1.152	1.193
0.00	0.10	1.221	0.969	0.994	1.034	1.075	1.113
0.05	0.10	1.216	0.995	1.018	1.040	1.069	1.103
0.10	0.10	1.220	1.061	1.061	1.073	1.091	1.117
0.15	0.10	1.226	1.149	1.133	1.125	1.134	1.142
0.20	0.10	1.218	1.185	1.157	1.138	1.137	1.142
-0.20	0.15	1.218	1.265	1.248	1.259	1.265	1.271
-0.15	0.15	1.202	1.182	1.193	1.224	1.239	1.245
-0.10	0.15	1.218	1.097	1.161	1.208	1.233	1.243
-0.05	0.15	1.220	1.031	1.077	1.144	1.178	1.201
-0.00	0.15	1.216	0.952	1.037	1.091	1.140	1.183
0.00	0.15	1.218	0.988	1.014	1.044	1.076	1.115
0.05	0.15	1.210	1.023	1.034	1.059	1.085	1.107
0.10	0.15	1.215	1.097	1.095	1.102	1.116	1.127
0.15	0.15	1.219	1.166	1.150	1.140	1.135	1.140
0.20	0.15	1.211	1.200	1.170	1.159	1.158	1.152

Note: MSE was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S15. Total Effective Sample Size of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at high baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0	219	192	163	133	97
-0.15	0.05	0	233	205	176	143	105
-0.10	0.05	0	246	219	188	155	113
-0.05	0.05	0	255	227	196	161	118
-0.00	0.05	0	261	234	203	166	121
0.00	0.05	0	255	229	201	166	119
0.05	0.05	0	253	228	199	164	118
0.10	0.05	0	247	222	193	159	114
0.15	0.05	0	240	216	188	154	107
0.20	0.05	0	230	206	178	144	100
-0.20	0.10	0	212	185	158	127	93
-0.15	0.10	0	226	199	170	138	100
-0.10	0.10	0	241	213	184	150	111
-0.05	0.10	0	252	225	194	159	116
-0.00	0.10	0	258	231	200	164	119
0.00	0.10	0	254	228	199	165	118
0.05	0.10	0	251	227	198	162	118
0.10	0.10	0	244	219	191	157	112
0.15	0.10	0	235	211	183	149	105
0.20	0.10	0	227	203	174	141	97
-0.20	0.15	0	204	178	151	121	88
-0.15	0.15	0	220	193	165	133	97
-0.10	0.15	0	235	208	179	145	106
-0.05	0.15	0	247	220	189	155	114
-0.00	0.15	0	258	230	199	162	118
0.00	0.15	0	254	229	200	165	118
0.05	0.15	0	249	224	196	161	115
0.10	0.15	0	241	217	189	155	111
0.15	0.15	0	232	208	179	145	103
0.20	0.15	0	222	197	169	136	94

Note: The effective sample size (ESS) was rounded down to the nearest integer; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S16. Power of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0.626	0.535	0.577	0.639	0.669	0.659
-0.15	0.05	0.624	0.628	0.646	0.662	0.690	0.676
-0.10	0.05	0.628	0.714	0.714	0.718	0.722	0.702
-0.05	0.05	0.634	0.776	0.756	0.742	0.724	0.708
-0.00	0.05	0.622	0.814	0.798	0.772	0.756	0.704
0.00	0.05	0.630	0.819	0.807	0.773	0.759	0.722
0.05	0.05	0.618	0.829	0.807	0.789	0.767	0.731
0.10	0.05	0.632	0.848	0.820	0.790	0.768	0.734
0.15	0.05	0.622	0.848	0.822	0.796	0.766	0.720
0.20	0.05	0.634	0.848	0.824	0.798	0.772	0.736
-0.20	0.10	0.634	0.497	0.559	0.640	0.668	0.680
-0.15	0.10	0.630	0.586	0.608	0.661	0.677	0.679
-0.10	0.10	0.632	0.676	0.686	0.710	0.704	0.698
-0.05	0.10	0.628	0.747	0.725	0.727	0.717	0.697
-0.00	0.10	0.620	0.791	0.773	0.759	0.739	0.715
0.00	0.10	0.622	0.828	0.810	0.772	0.766	0.728
0.05	0.10	0.628	0.837	0.819	0.795	0.771	0.730
0.10	0.10	0.626	0.842	0.826	0.800	0.776	0.721
0.15	0.10	0.626	0.846	0.826	0.796	0.764	0.730
0.20	0.10	0.628	0.840	0.818	0.788	0.762	0.733
-0.20	0.15	0.614	0.456	0.536	0.622	0.675	0.675
-0.15	0.15	0.622	0.540	0.586	0.647	0.671	0.677
-0.10	0.15	0.626	0.631	0.657	0.679	0.689	0.673
-0.05	0.15	0.624	0.724	0.726	0.716	0.710	0.690
-0.00	0.15	0.624	0.760	0.746	0.728	0.720	0.700
0.00	0.15	0.626	0.830	0.814	0.782	0.762	0.718
0.05	0.15	0.622	0.848	0.822	0.792	0.776	0.728
0.10	0.15	0.622	0.839	0.827	0.805	0.777	0.724
0.15	0.15	0.622	0.846	0.824	0.796	0.774	0.728
0.20	0.15	0.628	0.832	0.820	0.790	0.770	0.737

Note: power values were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S17. Type I error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0.043	0.025	0.029	0.039	0.047	0.047
-0.15	0.05	0.045	0.029	0.035	0.041	0.047	0.047
-0.10	0.05	0.043	0.035	0.037	0.047	0.047	0.049
-0.05	0.05	0.043	0.041	0.047	0.053	0.055	0.051
-0.00	0.05	0.045	0.049	0.051	0.051	0.053	0.051
0.00	0.05	0.045	0.059	0.055	0.057	0.055	0.051
0.05	0.05	0.043	0.075	0.071	0.061	0.053	0.047
0.10	0.05	0.043	0.091	0.081	0.067	0.057	0.053
0.15	0.05	0.045	0.091	0.083	0.069	0.067	0.055
0.20	0.05	0.043	0.111	0.099	0.079	0.071	0.061
-0.20	0.10	0.043	0.025	0.031	0.041	0.045	0.047
-0.15	0.10	0.043	0.029	0.033	0.043	0.047	0.045
-0.10	0.10	0.043	0.031	0.033	0.039	0.045	0.045
-0.05	0.10	0.043	0.037	0.041	0.047	0.047	0.049
-0.00	0.10	0.043	0.041	0.045	0.051	0.055	0.051
0.00	0.10	0.043	0.069	0.067	0.063	0.053	0.049
0.05	0.10	0.043	0.073	0.063	0.059	0.053	0.045
0.10	0.10	0.045	0.093	0.077	0.069	0.063	0.055
0.15	0.10	0.047	0.103	0.093	0.081	0.069	0.059
0.20	0.10	0.043	0.115	0.095	0.079	0.069	0.059
-0.20	0.15	0.043	0.027	0.031	0.041	0.043	0.043
-0.15	0.15	0.043	0.027	0.029	0.037	0.045	0.047
-0.10	0.15	0.043	0.031	0.033	0.035	0.047	0.049
-0.05	0.15	0.043	0.035	0.037	0.043	0.047	0.047
-0.00	0.15	0.045	0.041	0.047	0.047	0.053	0.051
0.00	0.15	0.045	0.073	0.065	0.063	0.053	0.045
0.05	0.15	0.043	0.091	0.075	0.071	0.057	0.049
0.10	0.15	0.045	0.099	0.083	0.075	0.063	0.055
0.15	0.15	0.043	0.109	0.095	0.073	0.071	0.059
0.20	0.15	0.045	0.101	0.095	0.077	0.063	0.053

Note: type I error were rounded to three decimal places; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S18. Bias of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0.411	-5.316	-3.884	-2.016	-0.803	-0.071
-0.15	0.05	0.384	-4.272	-3.359	-1.971	-0.957	-0.247
-0.10	0.05	0.431	-3.035	-2.380	-1.531	-0.784	-0.209
-0.05	0.05	0.440	-1.720	-1.366	-0.848	-0.465	-0.133
-0.00	0.05	0.381	-0.515	-0.442	-0.241	-0.136	0.019
0.00	0.05	0.444	0.948	0.783	0.614	0.467	0.349
0.05	0.05	0.390	2.015	1.668	1.321	0.984	0.714
0.10	0.05	0.414	3.052	2.482	1.953	1.465	1.059
0.15	0.05	0.381	3.625	2.975	2.333	1.783	1.296
0.20	0.05	0.449	4.187	3.405	2.709	2.080	1.537
-0.20	0.10	0.462	-5.648	-3.984	-2.021	-0.735	0.109
-0.15	0.10	0.447	-4.766	-3.592	-1.920	-0.856	-0.096
-0.10	0.10	0.446	-3.746	-2.953	-1.796	-0.914	-0.294
-0.05	0.10	0.391	-2.434	-1.933	-1.271	-0.590	-0.176
-0.00	0.10	0.403	-1.117	-0.861	-0.502	-0.252	0.003
0.00	0.10	0.421	1.381	1.162	0.902	0.670	0.466
0.05	0.10	0.416	2.439	2.004	1.584	1.175	0.865
0.10	0.10	0.394	3.381	2.750	2.200	1.646	1.211
0.15	0.10	0.406	3.857	3.187	2.518	1.928	1.403
0.20	0.10	0.424	4.314	3.530	2.777	2.148	1.609
-0.20	0.15	0.393	-5.932	-4.017	-1.945	-0.498	0.244
-0.15	0.15	0.447	-5.235	-3.846	-2.076	-0.874	-0.095
-0.10	0.15	0.455	-4.354	-3.339	-1.965	-0.954	-0.306
-0.05	0.15	0.429	-3.135	-2.495	-1.606	-0.836	-0.300
-0.00	0.15	0.377	-1.902	-1.511	-1.015	-0.538	-0.231
0.00	0.15	0.399	1.859	1.519	1.217	0.906	0.647
0.05	0.15	0.372	2.848	2.344	1.789	1.355	0.958
0.10	0.15	0.364	3.616	2.999	2.367	1.765	1.279
0.15	0.15	0.397	4.005	3.319	2.590	2.014	1.475
0.20	0.15	0.452	4.325	3.559	2.823	2.202	1.662

Note: Bias was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights; EBW_{MSDB} indicates the MSDB prior with weight in EB-rMAP method; BOX_{MSDB} indicates the MSDB prior with weight in BOX method; SAM_{MSDB} indicates the MSDB prior with weight in SAM method

Table S19. Mean Squared Error of the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	1.223	1.097	1.094	1.120	1.191	1.245
-0.15	0.05	1.220	0.966	0.977	1.077	1.156	1.199
-0.10	0.05	1.199	0.854	0.895	0.994	1.100	1.177
-0.05	0.05	1.219	0.794	0.848	0.960	1.067	1.137
-0.00	0.05	1.221	0.761	0.827	0.928	1.024	1.099
0.00	0.05	1.215	0.859	0.918	0.987	1.042	1.104
0.05	0.05	1.220	0.927	0.965	1.005	1.060	1.106
0.10	0.05	1.211	1.014	1.030	1.053	1.084	1.120
0.15	0.05	1.221	1.084	1.089	1.095	1.107	1.126
0.20	0.05	1.204	1.205	1.173	1.146	1.143	1.150
-0.20	0.10	1.203	1.154	1.117	1.163	1.210	1.249
-0.15	0.10	1.218	1.018	1.031	1.096	1.160	1.206
-0.10	0.10	1.221	0.909	0.933	1.016	1.120	1.178
-0.05	0.10	1.213	0.810	0.865	0.973	1.077	1.148
-0.00	0.10	1.215	0.774	0.840	0.948	1.060	1.133
0.00	0.10	1.222	0.873	0.923	0.988	1.042	1.094
0.05	0.10	1.215	0.926	0.958	0.986	1.029	1.077
0.10	0.10	1.219	1.045	1.052	1.070	1.091	1.112
0.15	0.10	1.216	1.138	1.133	1.115	1.118	1.131
0.20	0.10	1.226	1.236	1.201	1.170	1.158	1.162
-0.20	0.15	1.219	1.220	1.186	1.177	1.218	1.255
-0.15	0.15	1.230	1.090	1.089	1.143	1.195	1.241
-0.10	0.15	1.228	0.975	0.998	1.079	1.167	1.216
-0.05	0.15	1.220	0.866	0.909	1.006	1.109	1.176
-0.00	0.15	1.219	0.796	0.854	0.977	1.076	1.137
0.00	0.15	1.214	0.898	0.946	0.991	1.051	1.098
0.05	0.15	1.219	0.984	1.004	1.029	1.066	1.102
0.10	0.15	1.218	1.101	1.097	1.099	1.111	1.129
0.15	0.15	1.222	1.183	1.158	1.133	1.136	1.145
0.20	0.15	1.208	1.254	1.217	1.194	1.174	1.174

Note: MSE was multiplied by 100; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Table S20. Total Effective Sample Sizeof the multi-source dynamic borrowing Bayesian prior with Prior-Posterior consistency measure weights under various heterogeneity scenarios at low baseline imbalance using different threshold parameter.

γ_{diff}	γ_{RWD}	*Noborrow*	$PPCM_{MSDB}$				
			$\Gamma = 0.7$	$\Gamma = 0.75$	$\Gamma = 0.8$	$\Gamma = 0.85$	$\Gamma = 0.9$
-0.20	0.05	0	336	295	249	199	142
-0.15	0.05	0	363	321	272	219	156
-0.10	0.05	0	388	346	296	239	171
-0.05	0.05	0	409	368	320	260	183
-0.00	0.05	0	422	383	332	272	192
0.00	0.05	0	410	372	324	265	190
0.05	0.05	0	405	367	320	259	185
0.10	0.05	0	398	356	309	252	181
0.15	0.05	0	383	342	295	240	169
0.20	0.05	0	367	326	280	226	157
-0.20	0.10	0	323	284	240	191	135
-0.15	0.10	0	350	309	261	210	148
-0.10	0.10	0	378	335	286	231	165
-0.05	0.10	0	399	358	309	252	181
-0.00	0.10	0	415	373	324	264	189
0.00	0.10	0	408	368	321	264	190
0.05	0.10	0	406	366	317	258	184
0.10	0.10	0	392	351	302	244	174
0.15	0.10	0	374	332	287	234	164
0.20	0.10	0	357	318	274	221	153
-0.20	0.15	0	312	272	229	183	127
-0.15	0.15	0	338	297	251	201	141
-0.10	0.15	0	365	323	275	222	156
-0.05	0.15	0	390	349	299	242	172
-0.00	0.15	0	409	368	317	259	185
0.00	0.15	0	406	367	321	262	187
0.05	0.15	0	398	358	311	252	180
0.10	0.15	0	386	345	297	240	170
0.15	0.15	0	367	327	282	228	160
0.20	0.15	0	347	307	263	212	148

Note: The effective sample size (ESS) was rounded down to the nearest integer; $PPCM_{MSDB}$ indicates the multi-source dynamic borrowing Bayesian (MSDB) prior with Prior-Posterior consistency measure (PPCM) weights.

Part I The simulation setting and results of the small sample simulation scenarios

Different sample sizes were set to explore the practicability of the proposed method in application. Secifically, two small-sample-size scenarios ($N_{CTD} = 80, N_{ETD} = 100, N_{RWD} = 150$) and ($N_{CTD} = 100, N_{ETD} = 120, N_{RWD} = 170$) was explored respectively All the parameter setting scenarios are presented in Table 1. In simulation study, the parameter CM in the decision rule $P(\theta_{effect} > CM) > P_{CM}$ was set to 0, while P_{CM} was set to the value that makes the type I error in the No borrow method equal to 0.05, which is derived by computer simulation. The operational characteristics of $PPCM_{MSDB}$ under different heterogeneous scenarios with sample size setting I (80,100,120) and setting II (100,120,170) are demonstrated in Figure 1-Figure 2 and Table2-3.

Table 1. The parameter setting in samll sample size simulation.

Parameter	Setting	Annotation
K	$K = 4$	The number of time intervals in PWE model.
S	$S = 4$	The number of strata in propensity scores stratification.
α_0	$\alpha_0 = 0.5$	Effect of covariates on median survival time.
C_{rate}	$C_{rate} = 0.2$	Censoring rate.
N	① $N_{CTD} = 80, N_{ETD} = 100, N_{RWD} = 150$ ② $N_{CTD} = 100, N_{ETD} = 120, N_{RWD} = 170$	The sample in each group for three data set.
β_{CTD}	$\beta_{CTD} = 0.25$	Treatment effect on median survival time.
δ_{ETD}, δ_{RWD}	δ_{ETD}=0.1,$\delta_{\mathrm{RWD}} = 0.05$	Represent the high baseline imbalance.
γ_{ETD}, γ_{RWD}	$\gamma_{diff} = (0.05, 0.1, 0.15)$ ① $\gamma_{RWD} = (0, 0.05, 0.1, 0.15, 0.2)$ $\gamma_{ETD} = \gamma_{RWD} + \gamma_{diff}$ ② $\gamma_{RWD} = -(0, 0.05, 0.1, 0.15, 0.2)$ $\gamma_{ETD} = \gamma_{RWD} - \gamma_{diff}$	Represent the scenarios that trial effect higher than current trial and trial effect low than current trial respectively.
Γ	$\Gamma = 0.85$	The threshold parameter in PPCM weight.

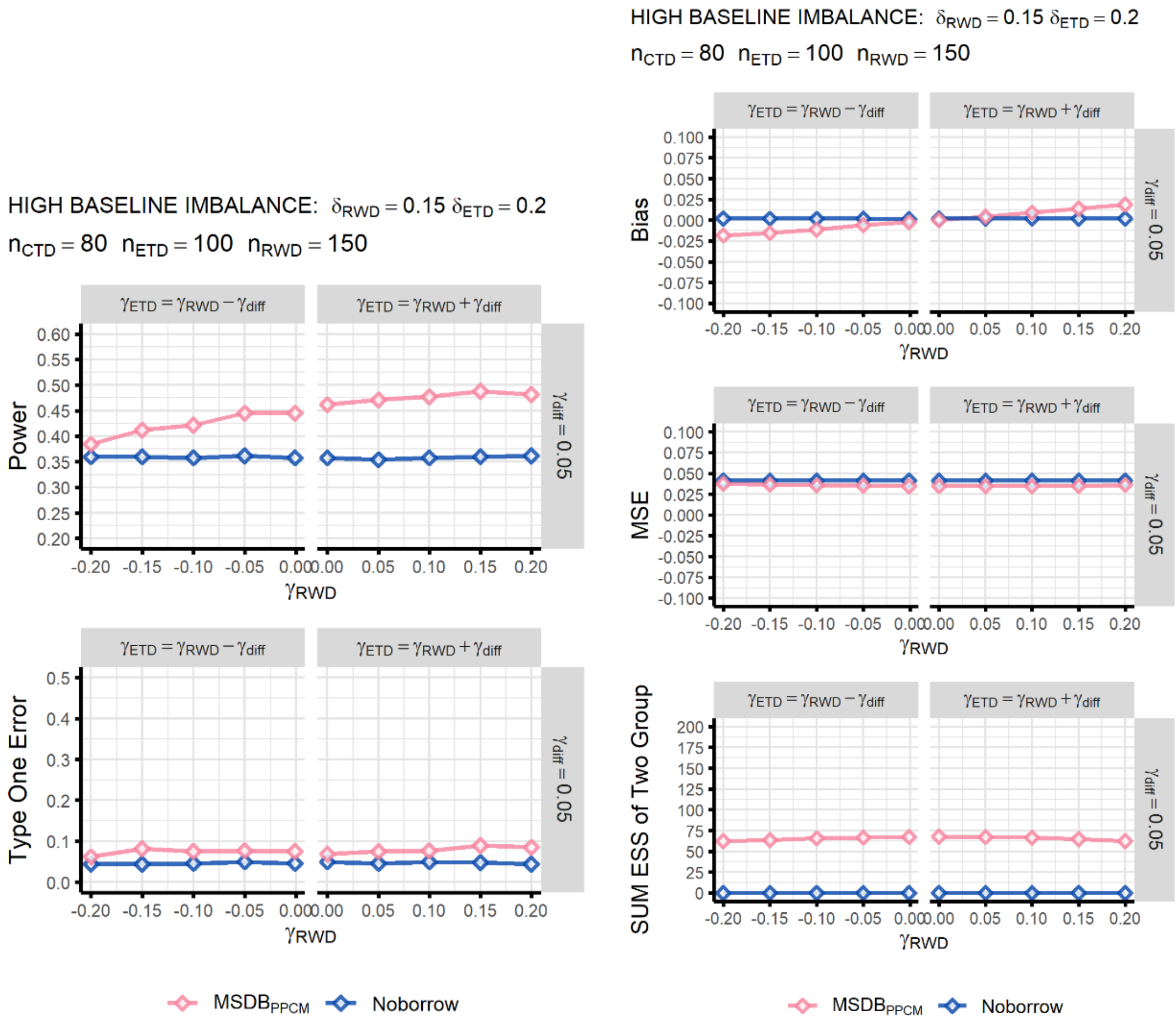

Figure 1. The operating characteristic of PPCM under different heterogeneous scenarios with sample size $N_{CTD} = 80, N_{ETD} = 100, N_{RWD} = 150$.

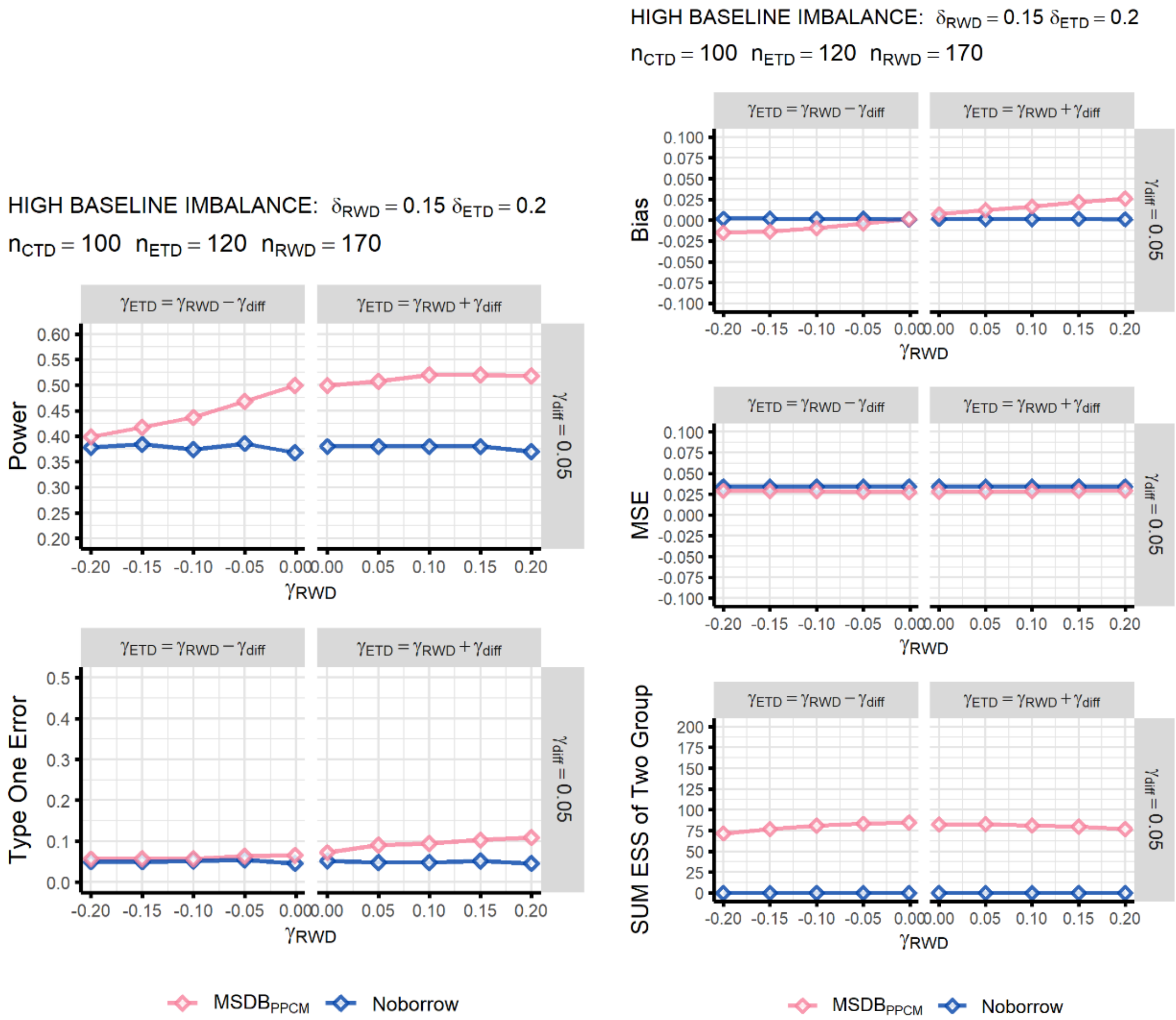

Figure 2. The operating characteristic of PPCM under different heterogeneous scenarios with sample size $N_{CTD} = 100, N_{ETD} = 120, N_{RWD} = 170$

Table 2. The operational characteristics of $PPCM_{MSDB}$ under different heterogeneous scenarios with sample size setting $N_{CTD} = 80, N_{ETD} = 100, N_{RWD} = 150$.

Method	γ_{diff}	γ_{RWD}	Power	T1E	Bias	MSE	Total-ESS
No-borrow	0.05	-0.20	0.360	0.044	0.002	0.041	-
		-0.15	0.360	0.044	0.002	0.041	-
		-0.10	0.358	0.046	0.002	0.041	-
		-0.05	0.362	0.050	0.002	0.041	-
		-0.00	0.358	0.046	0.002	0.041	-
		0.00	0.358	0.050	0.002	0.041	-
		0.05	0.354	0.046	0.002	0.042	-
		0.10	0.358	0.050	0.002	0.041	-
		0.15	0.360	0.048	0.002	0.041	-
		0.20	0.362	0.044	0.002	0.041	-
$PPCM_{MSDB}$	0.05	γ_{RWD}	0.384	0.062	-0.018	0.038	62
		-0.20	0.412	0.081	-0.015	0.037	64
		-0.15	0.422	0.075	-0.011	0.036	66
		-0.10	0.445	0.077	-0.006	0.035	67
		-0.05	0.445	0.075	-0.002	0.035	67
		-0.00	0.462	0.069	0.000	0.035	68
		0.00	0.471	0.075	0.004	0.035	67
		0.05	0.477	0.077	0.009	0.035	66
		0.10	0.488	0.089	0.014	0.035	65
		0.15	0.481	0.085	0.019	0.036	63

Table 3. The operational characteristics of $PPCM_{MSDB}$ under different heterogeneous scenarios with sample size setting $N_{CTD} = 100, N_{ETD} = 120, N_{RWD} = 170$.

Method	γ_{diff}	γ_{RWD}	Power	T1E	Bias	MSE	Total-ESS
No-borrow	0.05	-0.20	0.378	0.050	0.002	0.034	0
		-0.15	0.384	0.050	0.002	0.034	0
		-0.10	0.374	0.052	0.001	0.034	0
		-0.05	0.386	0.054	0.002	0.034	0
		-0.00	0.368	0.046	0.001	0.034	0
		0.00	0.380	0.052	0.002	0.034	0
		0.05	0.380	0.048	0.001	0.034	0
		0.10	0.380	0.048	0.001	0.034	0
		0.15	0.380	0.052	0.002	0.034	0
		0.20	0.370	0.046	0.001	0.034	0
$PPCM_{MSDB}$	0.05	γ_{RWD}	0.399	0.057	-0.015	0.029	72
		-0.20	0.418	0.057	-0.014	0.029	77
		-0.15	0.437	0.057	-0.009	0.029	81
		-0.10	0.468	0.063	-0.004	0.028	83
		-0.05	0.499	0.066	0.001	0.027	85
		-0.00	0.499	0.072	0.007	0.028	82
		0.00	0.507	0.091	0.012	0.028	83
		0.05	0.520	0.095	0.017	0.029	81
		0.10	0.520	0.103	0.022	0.029	80
		0.15	0.481	0.085	0.019	0.036	63

Part J The specific process of data generation in the example application.

For external RCT data, summary information published in trial ICARIA-MM[1] was used to generate simulated data, for example, dichotomous variables generated with a binomial distribution. PFS in Isa-Pd treatment group is 11.5 months and 6.5 months in Pd control group. With a Chinese prospective single-arm trial on Pd treatment[2], baseline covariates for the RCT data and endpoint for the Pd group with PFS of 5.7 months were generated. Endpoints for the Isa-Pd group were generated by assuming that the between-group effect was θ_{PFS}. By assuming that the treatment effects of both Isa-Pd and Pd in the real-world data are the same as in the RCT data, the data were generated based on a real-world study by Han et al[3].

Reference

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3. Han X, Jiang X, He J, et al. Clinical outcomes of pomalidomide-based and daratumumab-based therapies in patients with relapsed/refractory multiple myeloma: A real-world cohort study in China. *Cancer Med*. 2024;13(9):e7232. doi:10.1002/cam4.7232