

Interim sample size recalculation  
for linear and logistic regression models:  
a comprehensive Monte-Carlo study

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### Abstract

We propose a simple procedure for interim sample size recalculation when testing a hypothesis on a regression coefficient and explore its effects on type I and II errors. We consider hypothesis testing in linear and logistic regression models using the Wald test. We performed a comprehensive Monte-Carlo study comprised of 1092 experiments with 60,000 repetitions each. In these experiments we varied the number of predictors (1, 2, or 10), the type of predictors (binary and continuous), the magnitude of the tested regression coefficient, the degree of association between predictors, and the lower and upper limits on the total sample size.

## 1 Introduction

The sample size (SS) calculation is complicated by the presence of nuisance parameters. The values of these parameters are often estimated from external or internal pilot data which could substantially decrease the influence of erroneous assumptions on the values of these nuisance parameters.

In this manuscript we explore a “naive” approach to interim sample size re-estimation in linear and logistic regression models. This approach recalculates nuisance parameters at the interim analysis and updates the sample size bounded by the size of the internal pilot,  $n$ , and an upper bound,  $N_{max}$ , often chosen from budgetary or recruitment considerations. The benefit of sample size recalculation comes with a price, it inflates the type I error and power, and the final sample size becomes a random quantity.

We consider regression models of the form

$$E(Y|X_1, \dots, X_p) = g^{-1}(\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p), \quad (1)$$

where the mean of an outcome  $Y$  conditional on  $X_1, \dots, X_p$  is parameterized by a continuous monotone link function  $g(\cdot)$  and a linear combination of regression coefficients  $\beta_0, \dots, \beta_p$  and  $X_1, \dots, X_p$ . The logistic regression is defined by a LOGIT link function,  $g(EY) = \ln\left(\frac{EY}{1-EY}\right)$ ,

for a binary outcome. The gaussian linear regression is defined by the identity link function,  $g(EY) = EY$ , and a normal outcome.

Internal pilot designs have been addressed by many authors, see [10] and [2]. However, most research literature on internal pilot designs targets two group comparisons with random subject allocation. This focus comes from clinical trials, whereas the coverage of interim sample size recalculation for observational data is very sparse. A rare exception is the sample size re-estimation for a general linear model explored by [1]. An extension to linear mixed models was considered by [4]. A sample size recalculation for the analysis of covariance model (ANCOVA) was investigated by [3]. The above papers assume that model covariates are fixed quantities. The paper of [5] attempted to analyze the effect of random group allocation. Internal pilot based estimates of regression parameters and the distribution of covariates were used in [6] for resampling-based power estimation and consequent sample size estimation.

Literature suggests several approaches to sample size calculation for regression models. The parameters of interest in these approaches may be different.

A popular approach to sample size calculation was suggested in [9] where the effect size and sample size formula were taken from a single predictor regression model and adjusted for multiple predictors using the coefficient of multiple correlation between the predictor of interest and the other model predictors.

Shieh [11] suggested a sample size calculation formula for likelihood ratio tests in Generalized Linear Models (GLM). His focus on GLM and a regression coefficient as a parameter of interest coincides with our objective, however, his sample size formula was tailored to the likelihood ratio test whereas our main interest is on Wald test.

Sample size calculations often target the quality of outcome prediction, which is traditionally expressed by the coefficient of determination,  $R^2$ . Modified  $R^2$  measures such as the adjusted  $R^2$ , see [7], or the generalized  $R^2$ , see [8], are the popular extensions of  $R^2$  to non-linear models.

Our main interest lies in the analysis of association between  $X_1$  and  $Y$  adjusted for  $X_2, \dots, X_p$ . The conditional mean model (1) is fitted to assess this adjusted association, quantified by  $\beta_1$ . Sample sizes for testing the hypothesis about  $\beta_1$  are often based on asymptotic normality of  $\hat{\beta}_1$ , the Maximum Likelihood Estimator (MLE) of  $\beta_1$ . Asymptotic normality of  $\hat{\beta}_1$  justifies Wald, score, and asymptotic likelihood ratio tests. Consequently, the sample size formula is based on a  $z$ -approximation for testing  $H_0 : \beta_1 = 0$  versus some alternative  $H_1 : \beta_1 = \delta$ .

Even though, error minimization for regression modeling is not in the focus of this manuscript, we tied  $R^2$  with the values of  $\beta_1$  in simple linear regression models, and the generalized  $R^2$  with  $\beta_1$  in simple logistic regressions.

Section 2 presents sample size formulas for testing  $H_0$  on a linear or logistic regression model with the Wald test. Section 3 presents the results of comprehensive Monte-Carlo study performed for various artificial scenarios. The manuscript concludes with a short discussion in Section 5.

## 2 Sample size calculation for testing $H_0 : \beta_1 = 0$

We consider independent and identically distributed sampling when random variables  $(Y_i, X_{i1}, \dots, X_{ip})$ ,  $i = 1, \dots, n, \dots, N, \dots$ , are observed from a joint distribution  $F_{Y, X_1, \dots, X_p}(y, x_1, \dots, x_p)$ . In this scheme, we denote the internal pilot data sample size by  $n$  and the total sample size by  $N$ .

### Wald test

Regression models traditionally assume that the outcome  $Y$  is a random variable whereas the covariates  $X_1, \dots, X_p$  are quantities fixed by design. The randomness of covariates is often ignored and the modelling process is focused on a conditional mean defined by a conditional distribution  $F_{Y|X_1, \dots, X_p}(y|x_1, \dots, x_p)$ .

If a parametric family is assumed, then under some regularity conditions the limiting distribution of the maximum likelihood estimator (MLE),  $\hat{\mathbf{b}}$ , is normal,

$$\sqrt{n} \left( \hat{\mathbf{b}} - \mathbf{b} \right) \xrightarrow{d} N \left( 0, \mathcal{I}^{-1}(\mathbf{b}) \right), \quad (2)$$

where  $\mathcal{I}(\mathbf{b})$  is the (expected) Fisher information matrix,  $\mathbf{b} = (\beta_0, \beta_1, \dots, \beta_p)$ . The Fisher information is defined as

$$\mathcal{I}(\mathbf{b}) = -E_{Y, X_1, \dots, X_p} \left( \frac{\partial^2 \log f_{Y, X_1, \dots, X_p}}{\partial \mathbf{b} \partial \mathbf{b}^T} \right) \quad (3)$$

$$\begin{aligned} &= -E_{Y, X_1, \dots, X_p} \left( \frac{\partial^2 \log f_{X_1, \dots, X_p}}{\partial \mathbf{b} \partial \mathbf{b}^T} + \frac{\partial^2 \log f_{Y|X_1, \dots, X_p}}{\partial \mathbf{b} \partial \mathbf{b}^T} \right) \\ &= -E_{Y, X_1, \dots, X_p} \left( \frac{\partial^2 \log f_{Y|X_1, \dots, X_p}}{\partial \mathbf{b} \partial \mathbf{b}^T} \right), \end{aligned} \quad (4)$$

where  $f$  is a distribution (p.m.f. or p.d.f.) of a random variable defined by its subscript. The transition from (3) to (4) assumes that the distribution of covariates does not depend on  $\mathbf{b}$ . Thus, the difference with the Fisher information defined for a conditional on  $X_1, \dots, X_p$  model is that the dependence on  $X_1, \dots, X_p$  have to be integrated out.

Let  $\mathcal{I}^{-1}(\beta_1)$  be the second diagonal element of  $\mathcal{I}^{-1}(\mathbf{b})$ , the asymptotic variance of  $\hat{\beta}_1$ , then

$$\sqrt{n} \left( \hat{\beta}_1 - \beta_1 \right) \xrightarrow{d} N \left( 0, \mathcal{I}^{-1}(\beta_1) \right), \quad (5)$$

and the sample size formula for the Wald test is

$$N = \mathcal{I}^{-1}(\beta_1) \frac{(z_{1-\alpha/2} + z_{1-\beta})^2}{\delta^2}, \quad (6)$$

where  $\alpha$  is the type I error,  $\beta$  is the type II error where the absence of subscripts distinguishes it from the regression coefficients,  $z_\tau$  is a  $\tau$ -quantile of standard normal distribution,  $\delta$  is a (non-standardized) effect size.

Despite the simplicity of formula (6), we have not seen its use for sample size calculations in generalized linear models except for a multiple linear regression, see Section 2.

The practical use of (6) is complicated by the asymptotic nature of the test and the unknown  $\mathcal{I}^{-1}(\beta_1)$ . We use internal pilot data to estimate  $\mathcal{I}^{-1}(\beta_1)$  and recalculate the sample size. Regular regression model output contains a table of regression coefficients with estimates of their standard errors. From this table, the standard error of the internal pilot based estimate  $\hat{\beta}_1$  is  $SE(\hat{\beta}_1)$ . Then, we use  $n \left( SE(\hat{\beta}_1) \right)^2$  to approximate  $\mathcal{I}^{-1}(\beta_1)$  and calculate the total sample size. Then, the final formula for the total sample size is

$$N = n \left( SE(\hat{\beta}_1) \right)^2 \frac{(z_{1-\alpha/2} + z_{1-\beta})^2}{\delta^2}. \quad (7)$$

## Multiple linear regression

For a linear regression model

$$Y_i = \beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip} + \epsilon$$

with non-random covariates  $X_{i1}, \dots, X_{ip}$  and  $\epsilon \sim N(0, \sigma^2)$ , the Fisher information matrix for a single  $i^{th}$  observation  $(Y_i, X_{i1}, \dots, X_{ip})$  is a symmetric  $(p+1) \times (p+1)$  matrix

$$\mathcal{I}(\mathbf{b} | X_{i1}, \dots, X_{ip}) = \frac{1}{\sigma^2} \begin{pmatrix} X_{i0}X_{i0} & X_{i1}X_{i0} & \cdots & X_{ip}X_{i0} \\ X_{i0}X_{i1} & X_{i1}X_{i1} & \cdots & X_{ip}X_{i1} \\ \cdots & \cdots & \cdots & \cdots \\ X_{i0}X_{ip} & X_{i1}X_{ip} & \cdots & X_{ip}X_{ip} \end{pmatrix},$$

where  $X_{i0} = 1$ . Denote  $\mathbf{X}_i = (X_{i0}, \dots, X_{ip})^T$ , then  $\mathcal{I}(\mathbf{b} | X_{i1}, \dots, X_{ip}) = \sigma^{-2} \mathbf{X}_i \mathbf{X}_i^T$ .

If  $X_{i1}, \dots, X_{ip}$  are random variables, we need to integrate their distribution out,

$$\mathcal{I}(\mathbf{b}) = E_{X_{i1}, \dots, X_{ip}} \mathcal{I}(\mathbf{b} | X_{i1}, \dots, X_{ip}) = \sigma^{-2} E(\mathbf{X}_i \mathbf{X}_i^T). \quad (8)$$

The matrix of second moments  $E(\mathbf{X}_i \mathbf{X}_i^T)$  becomes the variance-covariance matrix of covariates when all covariates are centered,  $E(X_{ij}) = 0$  ( $j = 1, \dots, p$ ), except for the constant term  $X_{i0} = 1$ . The distribution of covariates in observational studies is often unknown. A simple solution is to plug-in internal pilot data based estimates of  $\sigma^2$  and  $E(\mathbf{X}_i \mathbf{X}_i^T)$  in Equation (8), then

$$\hat{\mathcal{I}}(\mathbf{b}) = \hat{\sigma}^{-2} n^{-1} \mathbf{X}_n \mathbf{X}_n^T,$$

where

$$\mathbf{X}_n = \begin{pmatrix} 1 & X_{11} & \cdots & X_{1p} \\ \cdots & \cdots & \cdots & \cdots \\ 1 & X_{n1} & \cdots & X_{np} \end{pmatrix}.$$

For a sufficiently large  $n$ ,  $\mathcal{I}^{-1}(\mathbf{b}) \approx n \hat{\sigma}^2 (\mathbf{X}_n^T \mathbf{X}_n)^{-1}$ , and

$$\sqrt{n} \left( \hat{\beta}_1 - \beta_1 \right) \overset{d}{\approx} N \left( 0, n \hat{\sigma}^2 (\mathbf{X}_n^T \mathbf{X}_n)_{(11)}^{-1} \right),$$

where  $(\mathbf{X}_n^T \mathbf{X}_n)_{(11)}^{-1}$  denotes the second diagonal element of  $(\mathbf{X}_n^T \mathbf{X}_n)^{-1}$ . For centered covari-

ates the use of some matrix algebra leads to

$$n (\mathbf{X}_n^T \mathbf{X}_n)_{(11)}^{-1} = \hat{\sigma}_{X_1}^{-2} \left( 1 - \hat{r}_{X_1|X_2, \dots, X_p}^2 \right)^{-1},$$

where  $\hat{\sigma}_{X_1}^2$  is the sample variance of  $X_1$  and  $\hat{r}_{X_1|X_2, \dots, X_p}^2$  is the sample proportion of variance in  $X_1$  explained by other covariates (the coefficient of multiple determination). Then,

$$N = \frac{\hat{\sigma}^2 (z_{1-\alpha/2} + z_{1-\beta})^2}{\delta^2 \hat{\sigma}_{X_1}^2 \left( 1 - \hat{r}_{X_1|X_2, \dots, X_p}^2 \right)} \quad (9)$$

is the pilot-data-based estimate of the sample size. We emphasize that (9) is just another form of formula (7) rewritten for multiple linear regression.

We also considered a “gold standard” sample size

$$N_{gold} = \frac{\sigma^2 (z_{1-\alpha/2} + z_{1-\beta})^2}{\delta^2 \sigma_{X_1}^2 \left( 1 - r_{X_1|X_2, \dots, X_p}^2 \right)} \quad (10)$$

calculated at known values of  $\sigma$ ,  $\sigma_{X_1}$ , and  $r_{X_1|X_2, \dots, X_p}$ . Obviously, the use of our “gold standard” is limited to simulation studies only, see the column “Target SS” in Tables 2-53.

## Multiple Logistic Regression

Multiple logistic regression is defined in Equation (1) by,  $g(p_i) = \log \left( \frac{p_i}{1-p_i} \right)$ , where

$$p_i = E(Y_i | X_{i1}, \dots, X_{ip}) = \frac{\exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})}{1 + \exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_p X_{ip})}.$$

The Fisher information matrix for a given design  $\mathbf{X}_n$  is

$$\mathcal{I}(\mathbf{b} | \mathbf{X}_n) = \mathbf{X}_n \text{diag}(p_i (1 - p_i)) \mathbf{X}_n^T.$$

When  $\mathbf{X}_n$  is a random matrix with i.i.d. rows, the sample mean

$$\hat{\mathcal{I}}(\mathbf{b}) = n^{-1} \sum_{i=1}^n \mathcal{I}(\hat{\mathbf{b}} | \mathbf{X}_n) = n^{-1} \sum_{i=1}^n \mathbf{X}_n \text{diag}(\hat{p}_i (1 - \hat{p}_i)) \mathbf{X}_n^T$$

is a consistent estimate of  $\mathcal{I}(\mathbf{b}) = E(\mathcal{I}(\mathbf{b} | \mathbf{X}_n))$  by the law of large numbers, where  $\hat{p}_i = \left( 1 + \exp(-\mathbf{X}_i^T \hat{\mathbf{b}}) \right)^{-1}$ . Then,  $\hat{\mathcal{I}}^{-1}(\beta_1)$ , the second diagonal element of  $\hat{\mathcal{I}}^{-1}(\mathbf{b})$ , is used in the sample size formula (6).

By analogy with the “gold standard” sample size formula (10) for linear gaussian regression, under known regression parameters and the distribution of covariates, we can find  $\mathcal{I}^{-1}(\beta_1)$  to calculate the the exact sample size, the column “Target SS” in Tables 54-79.

The “gold standard” formulas are not perfect due to their asymptotic and not finite sam-

ple optimality, however, known Fisher information makes these formulas data independent. Thus, these “gold standard” formulas can be considered as the target quantities in sample size re-estimation.

### 3 Simulation studies

Each simulation experiment was based on 60000 repetitions, 50000 under  $\beta_1 = 0$ , and 10000 under the alternative  $\beta_1 = \delta$ . This secured the Monte-Carlo standard error of 0.001 for estimating the type I error and 0.004 for estimating statistical power.

#### Covariates

Model covariates were generated from a multivariate normal, multinomial, or a mixture of normal distributions. To generate the distribution of  $X_1, \dots, X_p$  we first generated data from a multivariate normal distribution with zero mean, unit variances and an exchangeable correlation,  $r$ . Then, we categorized either  $X_1$  into  $B_1$  ( $= \text{sgn}(X_1)$ ) and/or  $X_j$  into  $B_j$  ( $= \text{sgn}(X_j)$ ;  $j = 2, \dots, p$ ) depending on a simulation experiment settings, where  $\text{sgn}(\cdot)$  is equal to 1 for a positive argument and  $-1$  for negative. For continuous predictors  $r$  was equal to 0 (independence), 0.4 (weak correlation) or 0.8 (strong correlation). To secure the Person correlation of 0.4 (0.8) between two binary predictors,  $B_j$  and  $B_l$  the original correlation between  $X_j$  and  $X_l$ , a.k.a. tetrachoric correlation, was set to 0.5878 (0.9511). To have the Pearson correlation of 0.4 (0.8) between a binary and a continuous predictors, say  $X_j$  and  $B_l$ , the original correlation between  $X_j$  and  $X_l$  was set to 0.5037 (0.9991).

The extremely strong correlation between  $X_j$  and  $X_l$  created a substantial rate of perfect collinearity between  $\text{sgn}(X_j)$  and  $\text{sgn}(X_l)$  in our simulation studies with multiple predictors. To solve this we used backward elimination of linearly dependent columns from the design matrix (except for  $X_1$ ) until a full rank design matrix was reached.

High collinearity creates a problem for estimating regression coefficients manifested in a higher variance.

In addition, the logistic regression periodically faced a complete separation problem, an common phenomenon in the presence of binary predictors and a rare, but possible, for continuous predictors. To avoid the separability issue we also performed backward elimination of linearly dependent columns until we reached full rank or until the design matrix had only the intercept column and  $X_1$ . If the rank of the two column matrix (intercept and  $X_1$ ) was one, then we called the results of testing inconclusive and excluded the case from consideration. To limit the number of inconclusive results we decreased the correlation between  $X_j$  and  $X_l$  from 0.9991 to 0.9 in logistic regression analyses, which generated the Pearson correlation of 0.72 between  $X_j$  and  $B_l$ .

#### The Effect Sizes

To choose effect sizes,  $\delta$ , for our modelling, we targeted specific values of  $R^2$ . We considered  $\beta_1 \in \{0.1429, 0.2294, 0.3333, 0.5, 1\}$  which defines  $R^2 \in \{0.02, 0.05, 0.1, 0.2, 0.5\}$ , respectively, in single predictor linear regression models. The definition of  $R^2$  via the ratio of mean

squared errors is not directly applicable to logistic regression models. However, a generalized  $R^2$  can be used instead. We found that the generalized  $R^2 \in \{0.02, 0.05, 0.1, 0.2\}$  for logistic regression model with a single continuous predictor is approximately reached at  $\beta_1 \in \{0.291, 0.469, 0.702, 1.127\}$  at  $n = 20$ . The  $\beta_1$  at the binary predictor leads to  $\beta_1 \in \{0.286, 0.459, 0.667, 1.003\}$  at  $n = 20$ . As the sample size increases, the generalized  $R^2$  converges to a constant, see Appendix. To keep track of the actual  $R^2$ , the columns  $E(R^2)$  in Tables 54-67 reports the averaged generalized  $R^2$ .

## Sample size recalculation and exceptions

We use the word “exceptions” to identify situations where the total sample size cannot be calculated due to some reasons, or the calculated number is above high or below low sample size boundaries. Inability to make a decision with the final sample is also classified as an exceptional case.

When an exception happens, an alternative action should be applied to resolve the situation. The possibility of this alternative action must be taken into account when the type I error and power are evaluated.

We mainly observed exceptions within the logistic regression framework. A few examples of exceptions at the internal pilot stage, and their solutions as listed below:

- Perfect co-linearity. This mainly happens between strongly associated categorical predictors.
  - *Solution:* Eliminate co-linear predictors from the model.
  - *Remark:* We use backward elimination, always keeping  $X_1$  in the model.
- High co-linearity.
  - *Solution:* When a standard error of  $\hat{\beta}_1$  is above 100 we eliminate a predictor strongly associated with  $X_1$ .
  - *Remark:* This is not exactly an exception, however, high co-linearity often leads to high standard errors, and thus to a sample size hitting the upper bound.
- All values of  $X_1$  or all values of  $Y$  are the same.
  - *Solution:* We set  $N = N_{max}$ .
  - *Remark:* This is one of the least informative situation on the total sample size.
- The separation or quasi-separation problem between  $Y$  and  $X_1$  in logistic regression models
  - *Solution:* We set  $N = N_{max}$ .
  - *Remark:* This decision, however, is not obvious. If, for example, all  $Y_i = X_{i1}$ , we may see overwhelming evidence of association between  $Y$  and  $X_1$  given  $P(Y)$  is bounded away from zero and one. The same situation ( $Y_i = X_{i1}$ ) with a few zeros or ones is an indication of an insufficient sample size.

Table 1: Table numbers classified by model, the number and type of predictors, Pearson correlation ( $r$ ),  $B_i = I(X_i > 0)$

Predictors	$r$	Linear $N_{max} = 300$	Linear $N_{max} = 600$	Logistic $N_{max} = 600$
$X_1$	0	2	28	54
$B_1$	0	3	29	55
$X_1, X_2$	0	4	30	56
$X_1, X_2$	0.4	5	31	57
$X_1, X_2$	0.8	6	32	58
$B_1, B_2$	0	7	33	59
$B_1, B_2$	0.4	8	34	60
$B_1, B_2$	0.8	9	35	61
$B_1, X_2$	0	10	36	62
$B_1, X_2$	0.4	11	37	63
$B_1, X_2$	0.8	12	38	64
$X_1, B_2$	0	13	39	65
$X_1, B_2$	0.4	14	40	66
$X_1, B_2$	0.8	15	41	67
$X_1, X_2, \dots, X_{10}$	0	16	42	68
$X_1, X_2, \dots, X_{10}$	0.4	17	43	69
$X_1, X_2, \dots, X_{10}$	0.8	18	44	70
$B_1, B_2, \dots, B_{10}$	0	19	45	71
$B_1, B_2, \dots, B_{10}$	0.4	20	46	72
$B_1, B_2, \dots, B_{10}$	0.8	21	47	73
$B_1, X_2, \dots, X_{10}$	0	22	48	74
$B_1, X_2, \dots, X_{10}$	0.4	23	49	75
$B_1, X_2, \dots, X_{10}$	—	24 ( $r = 0.8$ )	50 ( $r = 0.8$ )	76 ( $r = 0.72$ )
$X_1, B_2, \dots, B_{10}$	0	25	51	77
$X_1, B_2, \dots, B_{10}$	0.4	26	52	78
$X_1, B_2, \dots, B_{10}$	—	27 ( $r = 0.8$ )	53 ( $r = 0.8$ )	79 ( $r = 0.72$ )

- The sample size formula is applicable but the calculated sample size does not belong to the sample size range.

– *Solution:* If  $N < n_1$ , then  $N = n_1$ . If  $N > N_{max}$ , then  $N = N_{max}$ .

## Other settings

We explored three possibilities for the internal pilot sample size,  $n \in \{20, 50, 100\}$ . All results of our simulation experiments are reported in Tables 2-27 (Linear regression with  $N_{max} = 300$ ), Tables 28-53 (Linear regression with  $N_{max} = 600$ ), and Tables 54-79 (Logistic regression with  $N_{max} = 600$ ) with 12 to 15 experiments per table. The information on the type I error and power for multiple regression models are also summarized in Figures 1-10.

For convenience the summary of all Tables is presented in Table 1.



## 4 Empirical Conclusions

The Monte-Carlo Error for type I error assessments is 0.001, the Monte-Carlos error for power estimation was 0.004.

### Linear regression

In linear models, the type I error often stayed close to the desired level, which is consistent with previously published simulation results that used single predictor models. However, there were a few situations where the type I error was elevated.

**Single predictor:** Occasionally, the type I error was increased to 5.5% – 5.7% when the internal pilot was relatively small,  $n = 20$ , and the “gold standard” sample size was not high as well.

Table 2 shows that the “Target SS” is 70.68 for detecting  $\beta_1 = 0.3333$ , whereas actual total sample size had a mean of 83.46 with the SD of 41.33. The type I error for this model was 0.0547. Periodically, the total sample size falls below  $n$ , which as we see in all our simulations one of main contributor to the type I inflation. This problem increased at  $\beta_1 = 0.5$ , the type I error was estimated as 5.66%. A surprising effect shows up when the “Target SS” is equal to 7.86, which comes from a large effect size,  $\beta_1 = 1$ . This case had  $EN = 20.18$  and  $SD(EN) = 1.39$ , which means that with a rare exception our total sample size was equal to 20. This makes this scenario almost indistinguishable from the fixed sample size, and we are obviously overpowered in this case. The type I error was well controlled, the estimated type I error was 0.0494.

Similar inference is applicable for  $n = 50$ , but inflation of the type I error is present at a lower level, 0.0528 (at  $\beta_1 = 0.05$ ) and 0.0523 ( $\beta_1 = 0.0523$ ).

A linear regression model with a binary predictor, see Table 3, is slightly more sensitive to the type I error inflation, the type I error at  $n = 20$  is 0.0563 ( $\beta_1 = 0.2294$ ) and 0.0586 ( $\beta_1 = 0.3333$ ).

The upper bound for the total sample size for Tables 2 and 3 was equal to 300. This created situations with substantial underpowering. At  $n = 20$  and  $\beta_1 = 0.1429$ , the power for a continuous predictor was only 66% and 67.6% for a binary one. The increase in the internal pilot to  $n = 100$  provided a closer to the gold standard estimate of the total sample size, but did not resolve underpowering, we reached only 68.9% and 69.1% power for continuous and binary predictors, respectively.

Tables 28 and 28 report single predictors models for continuous and binary predictors, respectively, when the upper bound for the total sample size was 600. The conclusions about the type I error are essentially the same. The difference only in power properties. The upper bound of 600 observations was less likely to be reached and power less then 80% was seen only two times. For the continuous predictor the lowest power was observed at  $n = 20$  and  $\beta_1 = 0.1429$ , the same scenario for a binary predictor had power of 78.3%.

Overall, we observed underpowering when there was a substantial chance that the final sample size reached the upper bound. Similarly, overpowering could happen when the distribution of the final sample size “spilled over” the lower bound.

**Multiple predictors:** The inflation of the type I error at  $n = 20$  increases with increased number of predictors, see Tables 4-21. The worst type I error we have seen

is 0.0662, Table 24, at highly correlated predictors,  $B_1, X_2, \dots, X_{10}$ . The binary predictor of interest,  $B_1$ , was also associated with an increased type I error when compared to a continuous predictor  $X_1$ . As the size of internal pilot increases the inflation of type I error becomes less and less visible.

For illustrative convenience we also reported the type I error and power in eight figures, Figures 1 - 4 (linear regressions) and 7 - 10 (logistic regressions).

The type I errors for linear regression models with multiple predictors are reported in Figures 1 ( $X_1$  is binary) and 2 ( $X_1$  is continuous).

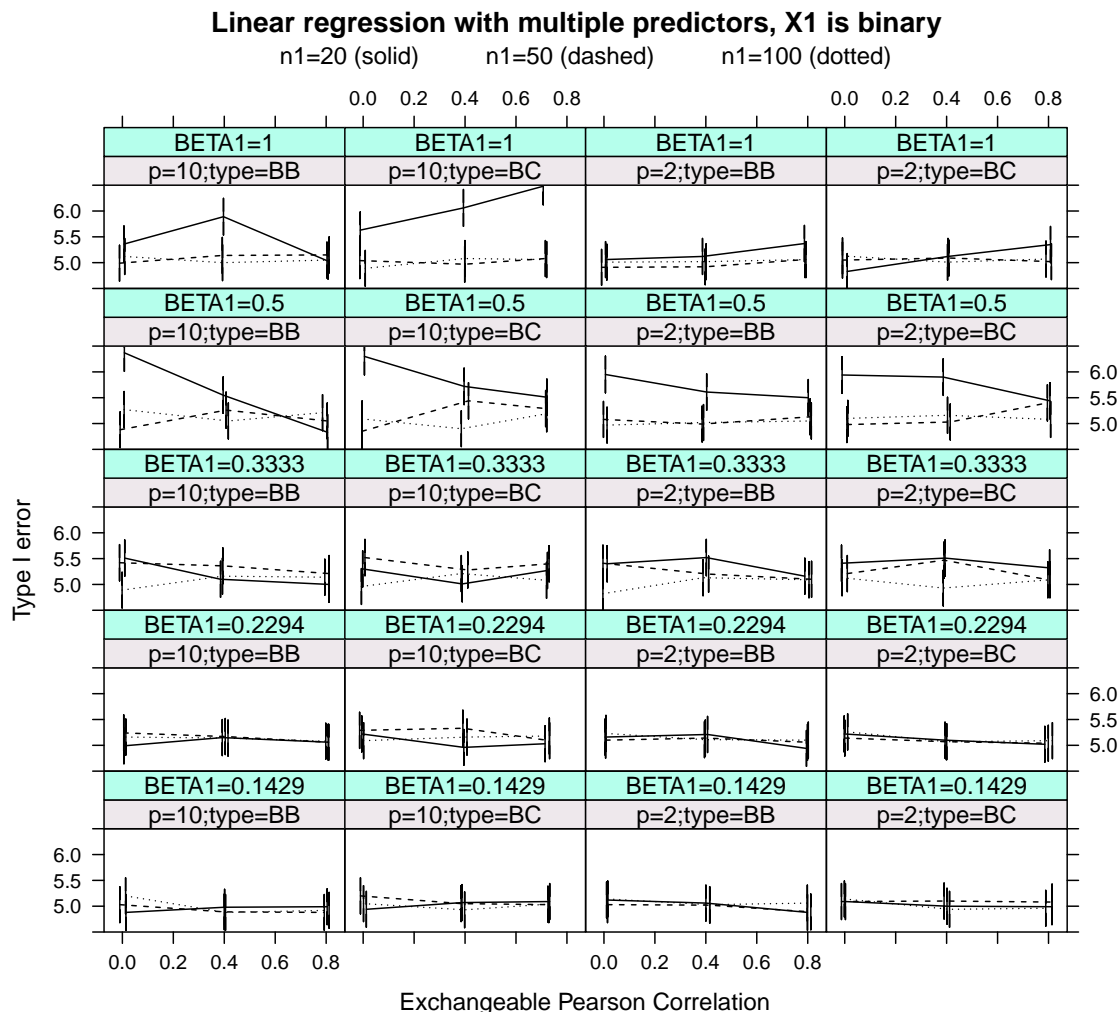


Figure 1: Type I error for testing a binary predictor of interest in multiple linear regression;  $p$  is the number of predictors; BB, all binary predictors; BC,  $X_1$  is binary and the rest are continuous predictors

Power for linear regression models with multiple predictors are reported in Figures 3 ( $X_1$  is binary) and 4 ( $X_1$  is continuous).

For large effect sizes, when the target sample size is close to  $n$  we often see power above the desired level. On the other hand, the sample sizes hitting the upper bound,  $N_{max}$ , lead to underpowered studies.

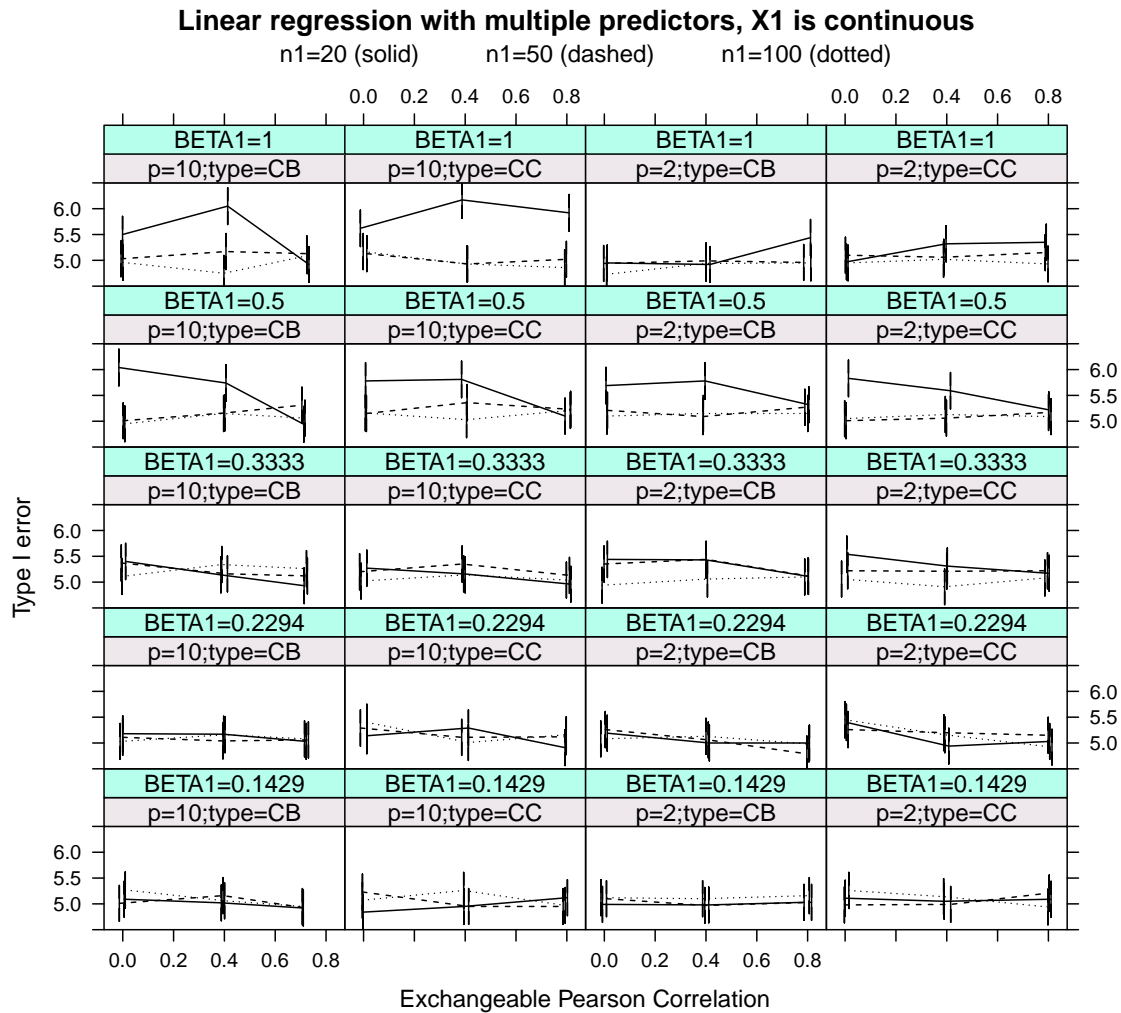


Figure 2: Type I error for testing a continuous predictor of interest in multiple linear regression;  $p$  is the number of predictors; CB,  $X_1$  is continuous and the rest are binary predictors; CC, all continuous predictors

The desired power is approximately achieved when the chances for  $N$  to be below  $n$  and above  $N_{max}$  are low. This is seen clearly for  $p = 2$  at  $\beta_1 = 0.2294$ .

## Logistic regression models

**Single predictor:** Single predictor models are reported in Tables 54 and 55 for continuous and binary predictors. Surprisingly the type I error was mainly below the designed 5%.

The lowest type I error for a single continuous predictor was 2.92% for  $n = 20$  with  $\beta_1 = 1.127$ . In this scenario  $E(N) = 39.21$  and  $SD(N) = 26.9$ , which means we observed a few  $N$  below  $n = 20$ . This effect was also associate with increased power, 84.4%. A good control of type I error and power was reached at  $n = 100$  with  $\beta_1 \in \{0.291, 0.469\}$ . These cases secured the type I error of 4.67% and 4.48%, and the power of 81.3% and 80.2%.

The smallest observed type I error for single binary predictor models was 3.7%, at  $n = 20$

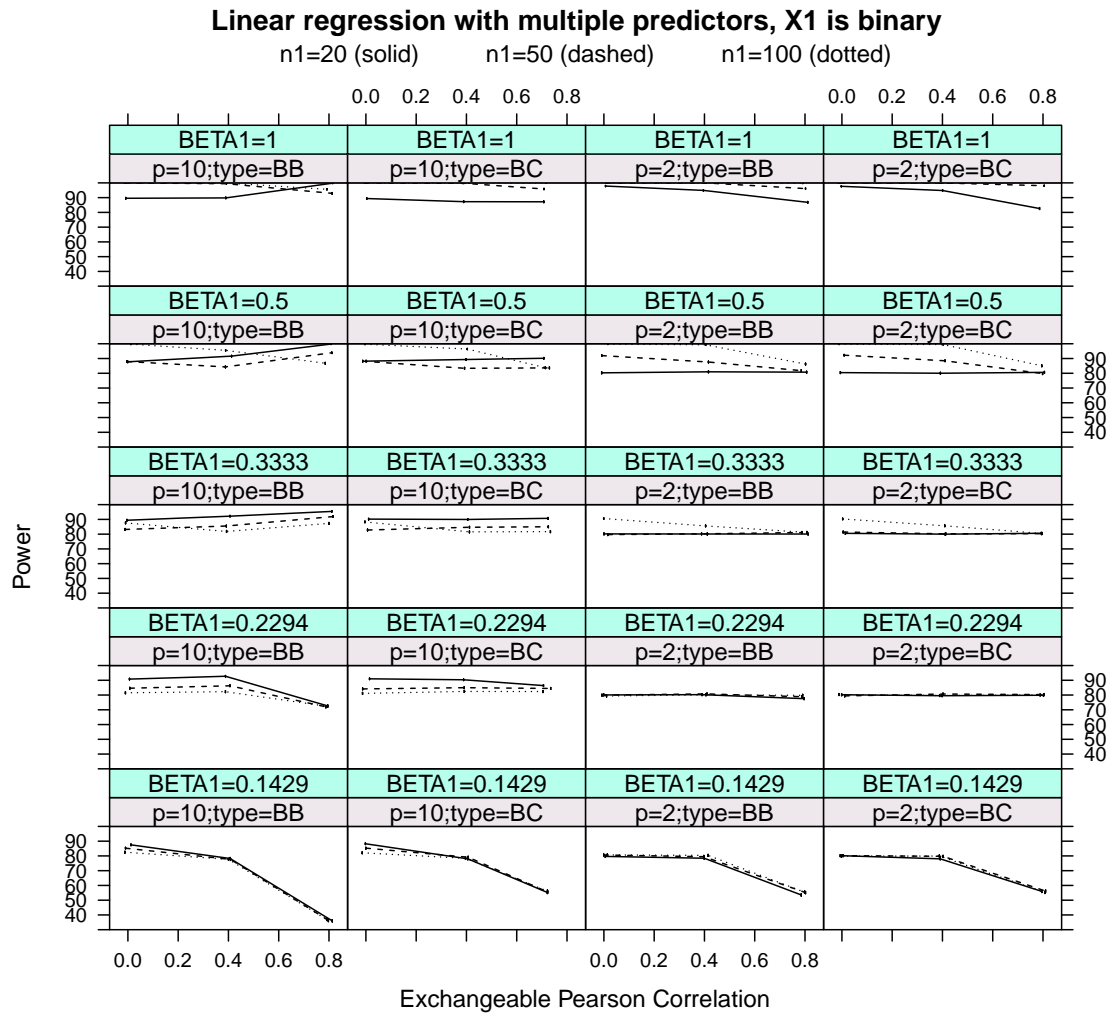


Figure 3: Power for testing a binary predictor of interest in multiple linear regression;  $p$  is the number of predictors; BB, all binary predictors; BC,  $X_1$  is binary and the rest are continuous predictors

and  $\beta_1 = 1$ . The power for this case was 83.7%. Good type I error and power were reached at  $n = 100$  with  $\beta_1 \in \{0.286, 0.459\}$ .

**Toy Example:** In most cases the type I and II errors are being inflated when the distribution of the total sample size,  $N$ , hits upper and/or lower bounds. Figures 5 and 6 show, respectively, a good and a bad scenario for interim sample size recalculations for logistic regression model.

The absence of exceptions along with the distribution of the total sample size fully contained between the  $n$  and  $N_{max}$  represent the most favorable scenario for interim sample size recalculation.

The bad scenario had two highly collinear binary predictors and a strong effect size. In our simulations, strong collinearity (when detected) was resolved by eliminating collinear predictors. The separability cases were addressed by administratively setting  $N = N_{max}$ . On the other hand, the high value of  $\beta_1$  often led to  $N < n_1$ , which was resolved by  $N = n_1$ .

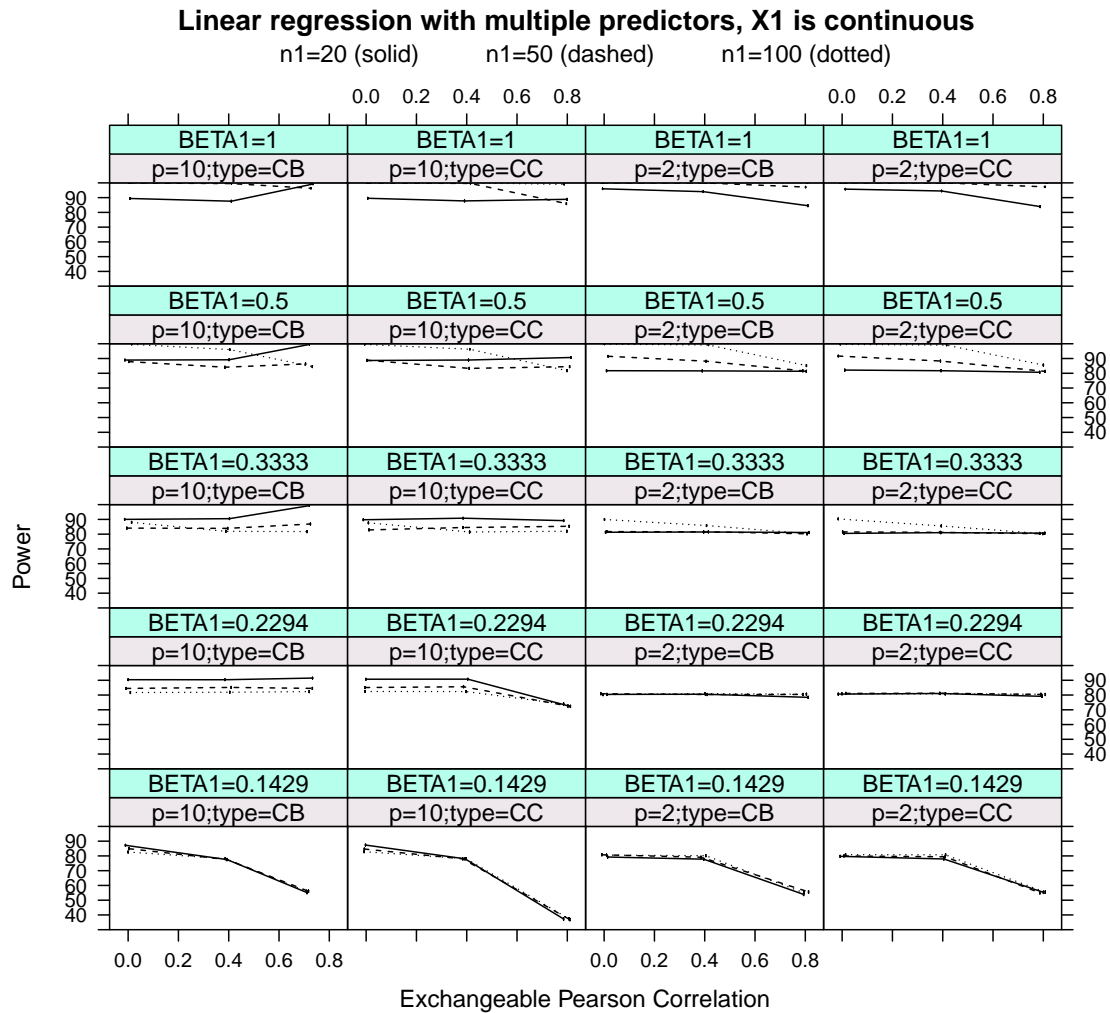


Figure 4: Power for testing a continuous predictor of interest in multiple linear regression;  $p$  is the number of predictors; CB,  $X_1$  is continuous and the rest are binary predictors; CC, all continuous predictors

Figure 6 reports one of worst situations we observed in our simulation studies.

**Multiple predictors:** The type I error for logistic regression models with multiple predictors are summarized in Figures 7 ( $X_1$  is binary) and 8 ( $X_1$  is continuous).

Figure 7 shows a surprising effect on type I error. It becomes much lower than 5% for highly correlated binary predictors at high values of  $\beta_1$ . The toy example (Figures 5 and 6) clearly shows that this comes from the high rate of exceptions. Similarly we observed excessive rates of exceptions for the cases of continuous  $X_1$  with high  $\beta_1$  and small  $n_1$ .

Power for logistic regression models with multiple predictors are reported in Figures 9 ( $X_1$  is binary) and 10 ( $X_1$  is continuous).

Power properties were reduced for cases with highly collinear binary predictors. This collinearity was often detected,  $B_2$  was removed from the model, which consequently led to a biased (downward) estimate of the variance of  $\hat{\beta}_1$  and to a lower final sample size.

We also observed lower power for the cases with a low effect size ( $\beta_1 = 0.286$ ). These

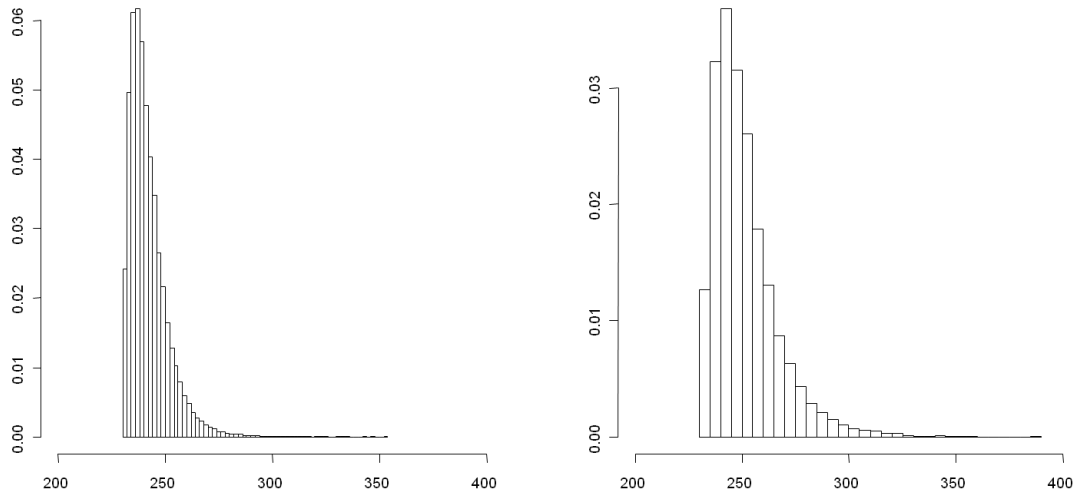


Figure 5: Logistic regression, two binary predictors,  $n_1 = 100$ ,  $\delta = 0.37$ ,  $r = 0$ , type I error = 4.9%, power=81.8%. Left panel presented the final sample size distribution under the null, the right panel is under the alternative hypothesis.

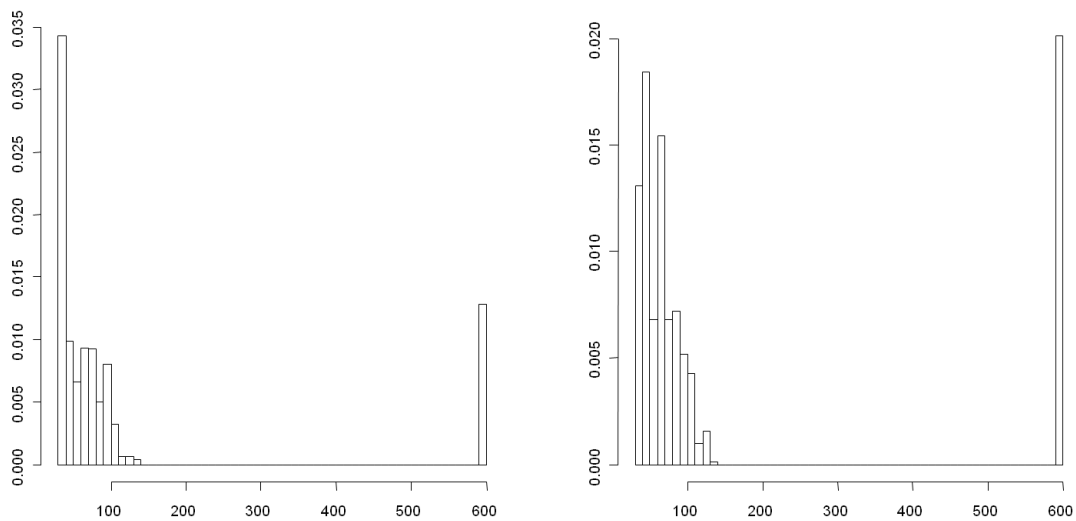


Figure 6: Logistic regression, two binary predictors,  $n_1 = 20$ ,  $\delta = 1$ ,  $r = 0.8$ , type I error = 1.3%, power=54.0%. Left panel presented the final sample size distribution under the null, the right panel is under the alternative hypothesis.

cases were mainly driven by the distribution of  $N$  and how often it hit  $N_{max}$ .

## 5 Discussion

### Logistic regression with multiple predictors, X1 is binary

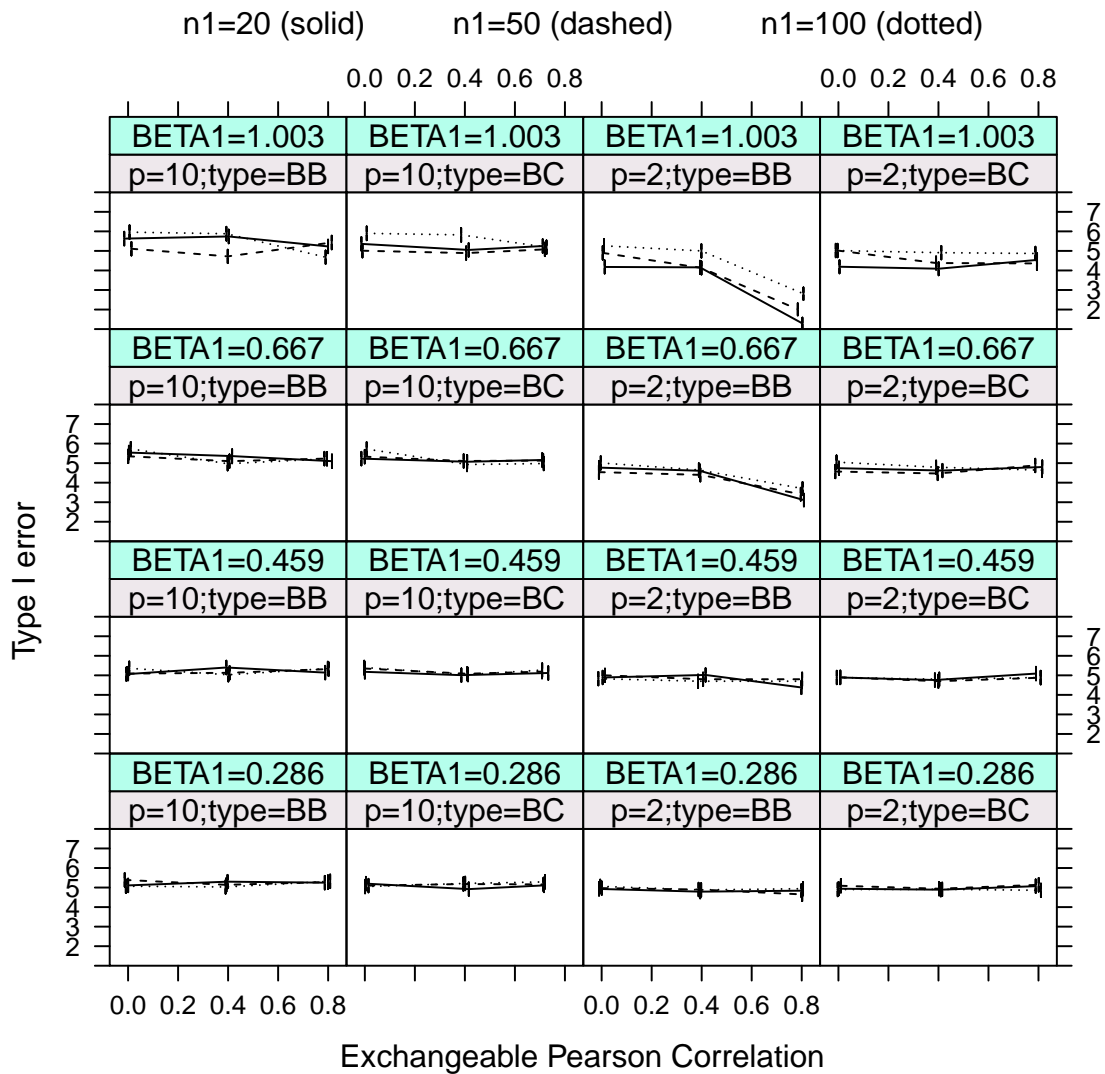


Figure 7: Type I error for testing a binary predictor of interest in multiple logistic regression;  $p$  is the number of predictors; BB, all binary predictors; BC,  $X_1$  is binary and the rest are continuous predictors



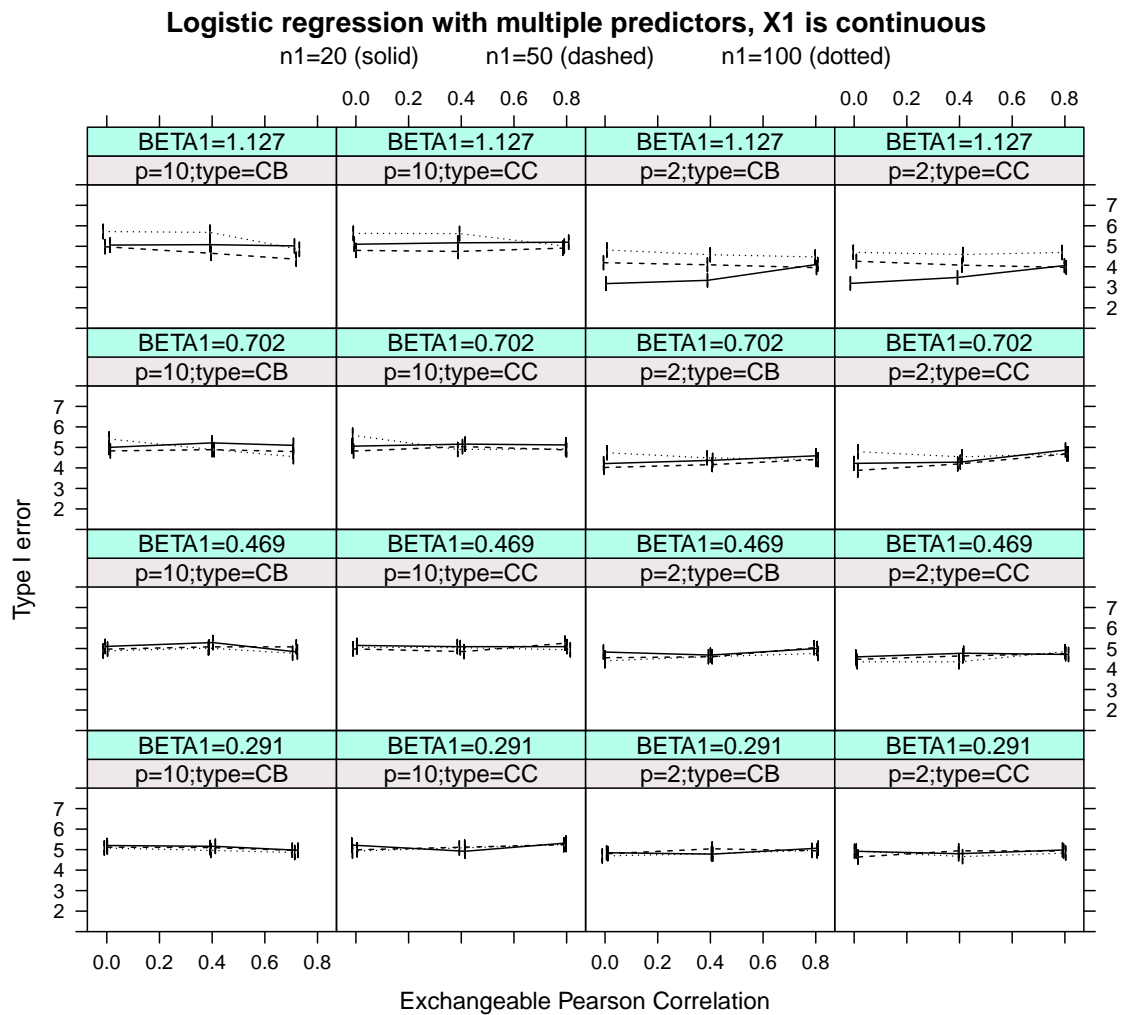


Figure 8: Type I error for testing a continuous predictor of interest in multiple logistic regression;  $p$  is the number of predictors; CB,  $X_1$  is continuous and the rest are binary predictors; CC, all continuous predictors

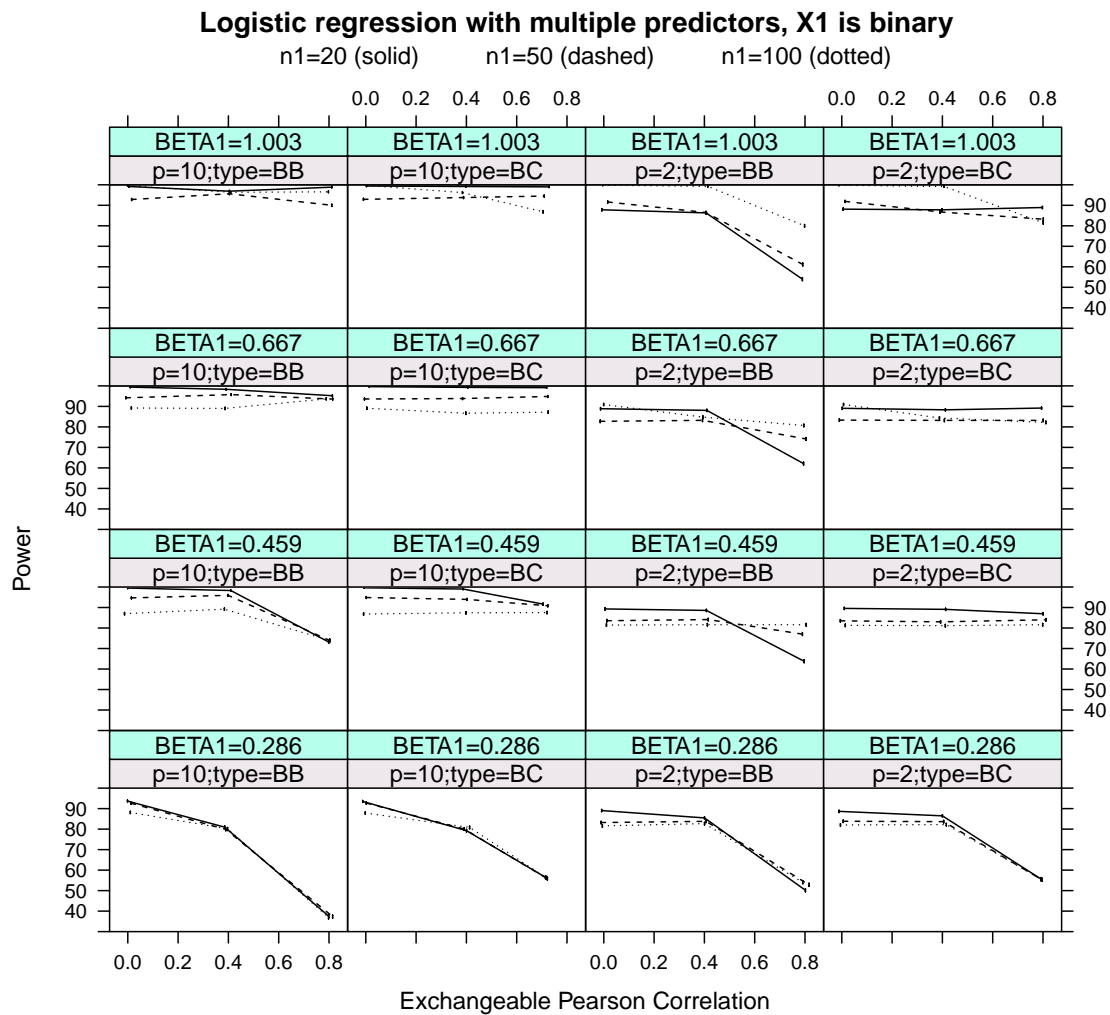


Figure 9: Power for testing a binary predictor of interest in multiple logistic regression;  $p$  is the number of predictors; BB, all binary predictors; BC,  $X_1$  is binary and the rest are continuous predictors

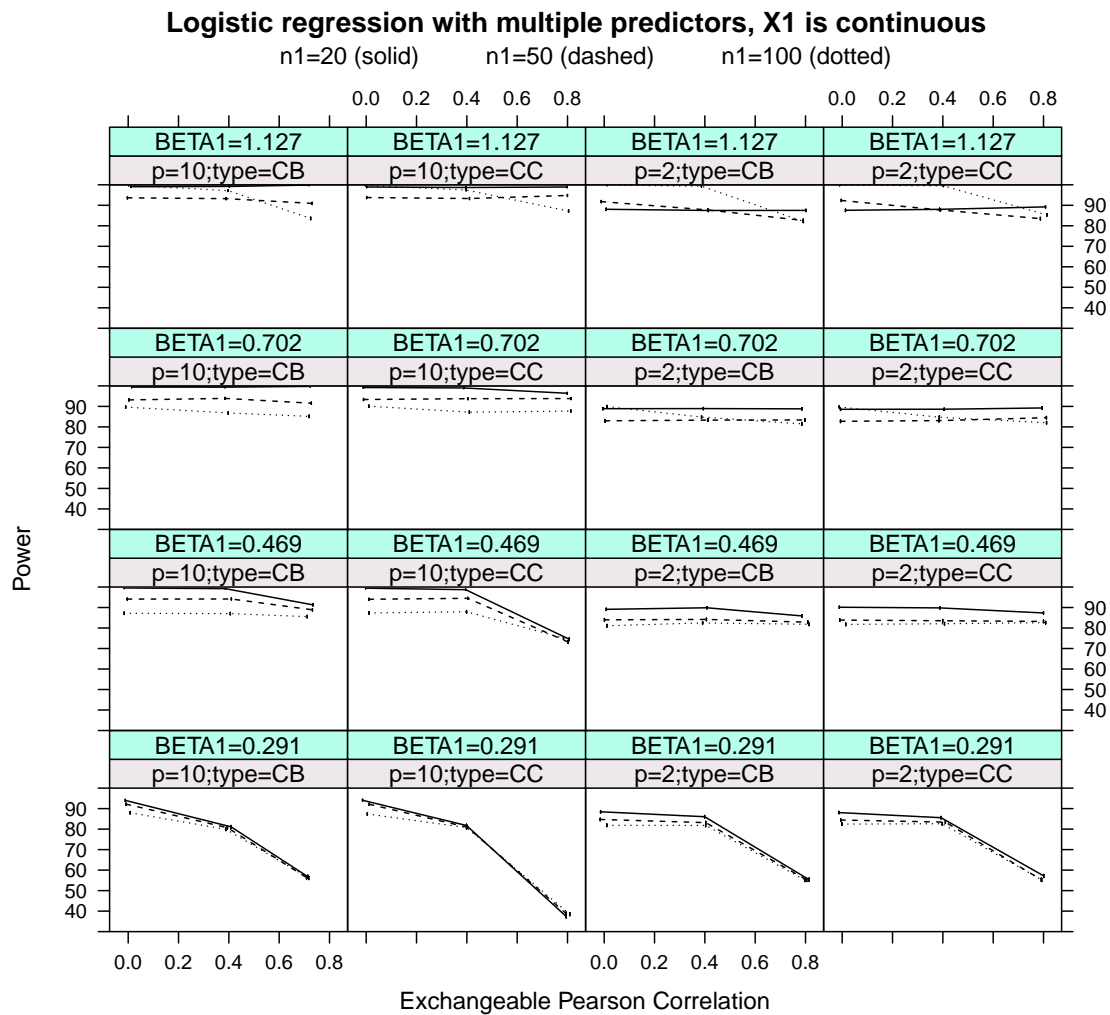


Figure 10: Power for testing a continuous predictor of interest in multiple logistic regression;  $p$  is the number of predictors; CB,  $X_1$  is continuous and the rest are binary predictors; CC, all continuous predictors

Naive internal pilot designs are commonly used in practice. These designs update the total sample size using new values of nuisance parameters at the interim analysis. These methods, however, use unadjusted sample size formulas and test statistics. This naive approach to sample size recalculation is known to inflate the type I and II errors. Meanwhile, a few statistical methods suggest various remedies for a better control of the size of the test and its power properties. We call these adjusted internal pilot designs as non-naive internal pilots designs.

Despite the existence of substantial amount of statistical literature on non-naive internal pilot designs, we did not see enough evidence to justify the use of non-naive internal pilot designs.

In this work, we did not make any modifications to the naive internal pilot designs. We investigated how much the type I and II errors are inflated under various scenarios with the use of the ordinary linear and logistic regression models as the primary analytic tools.

The detailed analysis is presented in Section 4. Overall our recommendations are the following.

- **Avoid small sizes for internal pilot designs.** We have seen substantial inflations and deflations for the size of the test. The type I error occasionally increased up to 6.62% in linear regression and decreased down to 1.3% in some instances of logistic regression model. When the internal pilot sample size increases, the type I error variations (inflation or deflation) becomes much smaller, which decreases the need for non-naive internal pilot designs.
- **Avoid collinearity.** Categorical predictors may generate perfectly collinear design matrices. The chance of observing collinearity increases with small sample sizes and for the cases or highly associated predictors. In the case of perfect collinearity we have to resolve the issue administratively, which may create a biased estimate of the total sample size. In a similar manner, high collinearity between predictors increases standard errors and leads to a skyrocketing sample size.
- **Avoid inadequate restrictions on the total sample size.** The distribution of the total sample size is a random quantity, and if it hits lower or upper bounds the type I and II errors are affected.
- **Use large internal pilots for logistic regression modelling of rare events.** Rare events lead to high variability in regression parameter estimation, elevated chances for quasi-separability and separability, and there is a substantial probability that no events are observed in the internal pilot.

We found that the recipe for a well control of type I and II errors in naive internal pilot designs include (1) a sufficiently large internal pilot sample size, (2) the distribution support of the total sample size ( $N$ ) fully located between the lower ( $n_1$ ) and upper ( $N_{max}$ ) bounds, and (3) very low probability exceptions.

The chance that the distribution of  $N$  hits the lower bound  $n_1$  is of a lesser concerns if the internal pilot is sufficiently large. The type I error inflation decreases with the increase of  $n_1$ .

Overall, naive internal pilot designs are useful and legitimate way for sample size recalculation provided that the aforementioned pitfalls are avoided.

## Appendix

The generalized  $R_G^2$  (see [8]) is defined by

$$R_G^2 = 1 - \left( \frac{L(0)}{L(\hat{\beta})} \right)^{2/n}, \quad (11)$$

where  $L(0)$  is the likelihood of the intercept-only model,  $L(\hat{\beta})$  is the likelihood based on the estimated model parameters. We consider a simple single predictor case when  $\beta = (\beta_0, \beta_1)$  and substitute  $L(\hat{\beta})$  with  $L(\beta)$  in Equation 11. Then, we consider

$$R_{\mathbf{X}}^2 = 1 - \left( \frac{L(0)}{L(\beta)} \right)^{2/n}, \quad (12)$$

where the subscript  $\mathbf{X}$  highlights the dependence on the design matrix. A bit of algebra leads to

$$\ln(1 - R_{\mathbf{X}}^2) = \frac{2}{n} \left\{ \ln L(0) - \ln L(\hat{\beta}) \right\} = \frac{1}{n} \left( -2 \ln \frac{L(\hat{\beta})}{L(0)} \right).$$

For an i.i.d. sample  $(Y_1, X_1), \dots, (Y_n, X_n)$  the log-likelihood conditional on  $X_i$  is

$$\ln L(\beta) = \sum_{i=1}^n \ln f(Y_i | \beta, X_i)$$

and

$$\begin{aligned} \ln(1 - R_{\mathbf{X}}^2) &= \frac{1}{n} \sum_{i=1}^n \left\{ -2 \ln \frac{f(Y_i | \hat{\beta}, X_i)}{f(Y_i | 0)} \right\} \\ &= -2 \int \ln \frac{f(y | \hat{\beta}, x)}{f(y | 0, x)} dP_n(x, y), \end{aligned} \quad (13)$$

where  $P_n(x, y)$  is the empirical measure with  $n^{-1}$  weights on  $(Y_i, X_i)$ . Under some regularity and properties of empirical processes, as  $n \rightarrow \infty$ ,

$$\ln(1 - R_{\mathbf{X}}^2) \rightarrow -2 \int \ln \frac{f(y | \beta, x)}{f(y | 0, x)} f(y | \beta, x) dy.$$

Thus, the generalized  $R^2$  asymptotically is independent of the sample size.

To establish connection between (12) and  $\beta_1$  we used numeric approximation and found that the generalized  $R^2 \in \{0.02, 0.05, 0.1, 0.2\}$  is approximately reached at  $\beta_1 \in \{0.291, 0.469, 0.702, 1.127\}$ , respectively at  $n = 20$ . For larger sample sizes and the same  $\beta_1$ , the generalized  $R^2$  become

Table 2: Linear regression with a single continuous predictor,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0505	0.6600	281.50	39.78	385.11
	0.2294	0.05	0.0504	0.7931	168.37	69.37	149.21
	0.3333	0.1	0.0547	0.7988	83.46	41.33	70.68
	0.5	0.2	0.0566	0.8170	38.21	18.49	31.36
	1	0.5	0.0494	0.9674	20.18	1.39	7.86
50	0.1429	0.02	0.0503	0.6831	292.65	20.67	385.11
	0.2294	0.05	0.0528	0.7935	159.25	45.81	149.21
	0.3333	0.1	0.0523	0.8106	76.08	21.24	70.68
	0.5	0.2	0.0501	0.9194	50.48	2.59	31.36
	1	0.5	0.0508	1	50	0	7.86
100	0.1429	0.02	0.0501	0.6892	297.41	10.35	385.11
	0.2294	0.05	0.0503	0.8074	154.56	31.08	149.21
	0.3333	0.1	0.0484	0.8988	100.46	2.80	70.68
	0.5	0.2	0.0488	0.9980	100	0	31.36
	1	0.5	0.0504	1	100	0	7.86

a little bit higher. This increase in  $R^2$  is not substantial, which means that the new values of  $\beta_1$  for other sample sizes are not needed.

Table 3: Linear regression with a single binary predictor,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	<i>Type I error</i>	<i>Power</i>	$E(N)$	$SD(N)$	<i>Target SS</i>
20	0.1429	0.02	0.0502	0.6757	286.84	31.70	384.36
	0.2294	0.05	0.0508	0.7833	157.06	52.59	149.15
	0.3333	0.1	0.0563	0.7902	75.26	26.14	70.65
	0.5	0.2	0.0586	0.7956	34.10	11.25	31.40
	1	0.5	0.0496	0.9825	20.01	1.20	7.85
50	0.1429	0.02	0.0515	0.6892	296.46	12.94	384.36
	0.2294	0.05	0.0519	0.7980	153.03	31.55	149.15
	0.3333	0.1	0.0544	0.7986	72.85	14.53	70.65
	0.5	0.2	0.0506	0.9306	50.03	0.44	31.40
	1	0.5	0.0515	1	50	0	7.85
100	0.1429	0.02	0.0502	0.6916	299.19	5.02	384.36
	0.2294	0.05	0.0518	0.7970	151.20	21.64	149.15
	0.3333	0.1	0.0497	0.9111	100.03	0.51	70.65
	0.5	0.2	0.0486	0.9986	100	0	31.40
	1	0.5	0.0509	1	100	0	7.85

Table 4: Linear regression with two independent continuous predictors,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0521	0.6674	283.91	37.52	384.58
	0.2294	0.05	0.0512	0.8022	176.83	71.56	149.03
	0.3333	0.1	0.0535	0.8094	88.57	45.11	70.69
	0.5	0.2	0.0579	0.8283	40.20	20.00	31.34
	1	0.5	0.0496	0.9596	20.26	1.70	7.86
50	0.1429	0.02	0.0497	0.6799	293.41	19.68	384.58
	0.2294	0.05	0.0516	0.8175	162.30	47.08	149.03
	0.3333	0.1	0.0528	0.8116	77.75	22.19	70.69
	0.5	0.2	0.0506	0.9157	50.56	2.84	31.34
	1	0.5	0.0506	0.9999	50	0	7.86
100	0.1429	0.02	0.0494	0.6810	297.65	9.77	384.58
	0.2294	0.05	0.0498	0.8072	155.91	31.67	149.03
	0.3333	0.1	0.0487	0.9019	100.53	3.07	70.69
	0.5	0.2	0.0491	0.9966	100	0	31.34
	1	0.5	0.0508	1	100	0	7.86

Table 5: Linear regression with two continuous predictors, Pearson correlation between the predictors = 0.4,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0511	0.5979	291.13	27.94	457.70
	0.2294	0.05	0.0515	0.7972	201.82	72.60	177.49
	0.3333	0.1	0.0557	0.8118	104.77	51.88	84.19
	0.5	0.2	0.0588	0.8135	47.40	24.18	37.45
	1	0.5	0.0506	0.9377	20.55	2.59	9.34
50	0.1429	0.02	0.0499	0.6165	298.03	10.48	457.70
	0.2294	0.05	0.0511	0.8022	191.49	52.31	177.49
	0.3333	0.1	0.0544	0.8092	92.27	27.06	84.19
	0.5	0.2	0.0498	0.8775	51.91	5.59	37.45
	1	0.5	0.0498	0.9999	50	0	9.34
100	0.1429	0.02	0.0494	0.6125	299.71	3.13	457.70
	0.2294	0.05	0.0517	0.8012	185.29	37.45	177.49
	0.3333	0.1	0.0515	0.8517	103.08	8.06	84.19
	0.5	0.2	0.0500	0.9919	100	0	37.45
	1	0.5	0.0492	1	100	0	9.34



Table 6: Linear regression with two continuous predictors, Pearson correlation between the predictors = 0.8,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0498	0.3156	299.84	0.64	1067.68
	0.2294	0.05	0.0489	0.6400	287.22	33.80	414.85
	0.3333	0.1	0.0505	0.7972	216.26	70.93	196.10
	0.5	0.2	0.0548	0.8087	100.51	53.75	87.23
	1	0.5	0.0555	0.8293	29.36	12.79	21.79
50	0.1429	0.02	0.0498	0.3111	300.00	0.02	1067.68
	0.2294	0.05	0.0502	0.6506	295.99	14.94	414.85
	0.3333	0.1	0.0494	0.8031	209.49	53.58	196.10
	0.5	0.2	0.0519	0.8086	95.38	28.18	87.23
	1	0.5	0.0495	0.9736	50.02	0.41	21.79
100	0.1429	0.02	0.0503	0.3105	300	0	1067.68
	0.2294	0.05	0.0514	0.6584	298.91	6.58	414.85
	0.3333	0.1	0.0516	0.8067	204.36	40.22	196.10
	0.5	0.2	0.0507	0.8437	104.12	9.27	87.23
	1	0.5	0.0483	0.9998	100	0	21.79

Table 7: Linear regression with two independent binary predictors,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0515	0.6706	288.52	30.12	384.36
	0.2294	0.05	0.0514	0.8081	166.85	57.89	149.15
	0.3333	0.1	0.0551	0.8098	80.03	29.73	70.65
	0.5	0.2	0.0585	0.8008	36.17	12.89	31.40
	1	0.5	0.0486	0.9762	20.03	0.50	7.85
50	0.1429	0.02	0.0493	0.6841	296.88	12.24	384.36
	0.2294	0.05	0.0505	0.8048	156.10	32.79	149.15
	0.3333	0.1	0.0536	0.8012	74.53	15.25	70.65
	0.5	0.2	0.0500	0.9291	50.05	0.58	31.40
	1	0.5	0.0492	1	50	0	7.85
100	0.1429	0.02	0.0520	0.6936	299.24	4.87	384.36
	0.2294	0.05	0.0518	0.7919	152.57	22.08	149.15
	0.3333	0.1	0.0493	0.9116	100.04	0.54	70.65
	0.5	0.2	0.0506	0.9976	100	0	31.40
	1	0.5	0.0498	1	100	0	7.85

Table 8: Linear regression with two binary predictors, Pearson correlation between the predictors = 0.4 (tetrachoric correlation = 0.5878),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0502	0.6074	293.42	23.06	457.61
	0.2294	0.05	0.0507	0.8057	196.93	67.10	177.69
	0.3333	0.1	0.0535	0.8014	100.26	46.99	84.18
	0.5	0.2	0.0578	0.8111	45.57	24.15	37.40
	1	0.5	0.0514	0.9519	20.68	8.41	9.35
50	0.1429	0.02	0.0488	0.6238	299.05	6.66	457.61
	0.2294	0.05	0.0513	0.8020	188.28	45.50	177.69
	0.3333	0.1	0.0540	0.8075	90.01	23.10	84.18
	0.5	0.2	0.0508	0.8821	51.19	4.24	37.40
	1	0.5	0.0524	0.9998	50	0	9.35
100	0.1429	0.02	0.0494	0.6209	299.92	1.55	457.61
	0.2294	0.05	0.0506	0.8065	183.26	31.62	177.69
	0.3333	0.1	0.0517	0.8513	101.87	5.74	84.18
	0.5	0.2	0.0505	0.9935	100	0	37.40
	1	0.5	0.0496	1	100	0	9.35

Table 9: Linear regression with two binary predictors, Pearson correlation between the predictors = 0.8 (tetrachoric correlation = 0.9511),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0496	0.3154	299.53	5.94	1066.30
	0.2294	0.05	0.0501	0.6061	279.60	43.74	415.22
	0.3333	0.1	0.0529	0.7875	214.63	81.50	196.77
	0.5	0.2	0.0544	0.8103	129.42	86.09	87.35
	1	0.5	0.0557	0.8576	62.84	89.82	21.83
50	0.1429	0.02	0.0488	0.3184	300.00	0.64	1066.30
	0.2294	0.05	0.0498	0.6372	291.21	24.26	415.22
	0.3333	0.1	0.0512	0.8033	211.15	66.65	196.77
	0.5	0.2	0.0512	0.8219	108.10	57.39	87.35
	1	0.5	0.0490	0.9632	53.46	21.37	21.83
100	0.1429	0.02	0.0480	0.3132	300	0	1066.30
	0.2294	0.05	0.0502	0.6514	296.33	13.46	415.22
	0.3333	0.1	0.0526	0.7958	208.47	55.17	196.77
	0.5	0.2	0.0512	0.8672	111.88	26.59	87.35
	1	0.5	0.0490	0.9971	100.03	1.73	21.83

Table 10: Linear regression with two independent predictors (binary and continuous), the predictor of interest is binary,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0514	0.6729	288.23	38.38	384.36
	0.2294	0.05	0.0503	0.8008	167.12	57.49	149.15
	0.3333	0.1	0.0555	0.8059	79.92	29.32	70.65
	0.5	0.2	0.0594	0.7992	36.18	12.80	31.40
	1	0.5	0.0510	0.9768	20.03	1.31	7.85
50	0.1429	0.02	0.0501	0.6946	296.78	12.57	384.36
	0.2294	0.05	0.0514	0.7992	155.85	32.89	149.15
	0.3333	0.1	0.0536	0.8037	74.40	15.23	70.65
	0.5	0.2	0.0502	0.9275	50.05	0.59	31.40
	1	0.5	0.0491	1	50	0	7.85
100	0.1429	0.02	0.0519	0.6966	299.28	4.76	384.36
	0.2294	0.05	0.0514	0.8045	152.76	21.98	149.15
	0.3333	0.1	0.0509	0.9016	100.04	0.60	70.65
	0.5	0.2	0.0492	0.9987	100	0	31.40
	1	0.5	0.0484	1	100	0	7.85

Table 11: Linear regression with two predictors (binary and continuous), the predictor of interest is binary, Pearson correlation between the predictors = 0.4 (original correlation = 0.5037),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0505	0.6073	293.40	23.14	458.25
	0.2294	0.05	0.0510	0.7999	195.05	65.22	177.87
	0.3333	0.1	0.0552	0.7967	96.67	40.36	84.21
	0.5	0.2	0.0565	0.8080	43.54	17.94	37.43
	1	0.5	0.0495	0.9482	20.18	1.29	9.37
50	0.1429	0.02	0.0500	0.6151	299.15	6.29	458.25
	0.2294	0.05	0.0517	0.8020	186.46	43.36	177.87
	0.3333	0.1	0.0524	0.8065	88.91	21.08	84.21
	0.5	0.2	0.0507	0.8816	50.89	3.21	37.43
	1	0.5	0.0511	0.9999	50	0	9.37
100	0.1429	0.02	0.0506	0.6182	299.92	1.49	458.25
	0.2294	0.05	0.0520	0.7896	182.36	30.05	177.87
	0.3333	0.1	0.0506	0.8527	101.62	5.01	84.21
	0.5	0.2	0.0472	0.9949	100	0	37.43
	1	0.5	0.0511	1	100	0	9.37

Table 12: Linear regression with two predictors (binary and continuous), the predictor of interest is binary, Pearson correlation between the predictors = 0.8 (original correlation = 0.9991),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0489	0.3179	299.94	1.98	1052.06
	0.2294	0.05	0.0501	0.6451	289.09	30.03	408.97
	0.3333	0.1	0.0515	0.7946	212.20	66.78	193.72
	0.5	0.2	0.0568	0.8061	101.79	43.46	86.16
	1	0.5	0.0554	0.8340	27.27	9.72	21.54
50	0.1429	0.02	0.0499	0.3136	300	0	1052.06
	0.2294	0.05	0.0493	0.6532	297.11	12.26	408.97
	0.3333	0.1	0.0511	0.7986	204.51	47.42	193.72
	0.5	0.2	0.0526	0.8100	92.05	23.10	86.16
	1	0.5	0.0519	0.9779	50.00	0.07	21.54
100	0.1429	0.02	0.0488	0.3163	300	0	1052.06
	0.2294	0.05	0.0498	0.6650	299.39	4.56	408.97
	0.3333	0.1	0.0514	0.8037	199.78	34.08	193.72
	0.5	0.2	0.0509	0.8451	102.43	6.38	86.16
	1	0.5	0.0504	0.9999	100	0	21.54

Table 13: Linear regression with independent predictors (binary and continuous), the predictor of interest is continuous,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0510	0.6602	283.63	38.05	384.02
	0.2294	0.05	0.0505	0.8109	177.43	71.87	149.09
	0.3333	0.1	0.0547	0.8133	88.66	45.29	70.56
	0.5	0.2	0.0563	0.8219	40.22	20.21	31.34
	1	0.5	0.0511	0.9590	20.25	1.69	7.85
50	0.1429	0.02	0.0518	0.6701	293.37	19.84	384.02
	0.2294	0.05	0.0520	0.8045	161.84	46.86	149.09
	0.3333	0.1	0.0529	0.8140	77.91	22.33	70.56
	0.5	0.2	0.0496	0.9174	50.58	2.89	31.34
	1	0.5	0.0502	1	50	0	7.85
100	0.1429	0.02	0.0497	0.6849	297.56	10.15	384.02
	0.2294	0.05	0.0516	0.8111	155.86	31.48	149.09
	0.3333	0.1	0.0496	0.9008	100.53	3.02	70.56
	0.5	0.2	0.0502	0.9979	100	0	31.34
	1	0.5	0.0510	1	100	0	7.85

Table 14: Linear regression with two predictors (continuous and binary), the predictor of interest is continuous, Pearson correlation between the predictors = 0.4 (original correlation = 0.5037),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0513	0.6030	291.16	27.89	458.75
	0.2294	0.05	0.0518	0.7942	201.45	72.39	178.24
	0.3333	0.1	0.0537	0.8163	105.01	52.59	84.22
	0.5	0.2	0.0576	0.8183	47.60	24.30	37.45
	1	0.5	0.0506	0.9386	20.57	2.65	9.37
50	0.1429	0.02	0.0512	0.6204	298.10	10.35	458.75
	0.2294	0.05	0.0512	0.8011	191.60	52.09	178.24
	0.3333	0.1	0.0541	0.8115	92.03	27.08	84.22
	0.5	0.2	0.0506	0.8862	52.02	5.82	37.45
	1	0.5	0.0497	0.9997	50	0	9.37
100	0.1429	0.02	0.0481	0.6128	299.72	3.18	458.75
	0.2294	0.05	0.0514	0.8100	185.74	37.36	178.24
	0.3333	0.1	0.0516	0.8646	103.12	8.09	84.22
	0.5	0.2	0.0502	0.9919	100	0	37.45
	1	0.5	0.0507	1	100	0	9.37

Table 15: Linear regression with two predictors (continuous and binary), the predictor of interest is continuous, Pearson correlation between the predictors = 0.8 (original correlation = 0.9991),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0510	0.3162	299.77	4.37	1052.62
	0.2294	0.05	0.0507	0.6410	285.53	36.52	408.51
	0.3333	0.1	0.0508	0.8045	215.12	73.92	193.89
	0.5	0.2	0.0539	0.8127	111.57	59.11	86.19
	1	0.5	0.0571	0.8481	30.27	14.78	21.53
50	0.1429	0.02	0.0491	0.3146	300.00	0.02	1052.62
	0.2294	0.05	0.0488	0.6516	294.59	18.21	408.51
	0.3333	0.1	0.0523	0.8109	208.59	56.84	193.89
	0.5	0.2	0.0534	0.8180	95.52	31.07	86.19
	1	0.5	0.0505	0.9732	50.04	0.71	21.53
100	0.1429	0.02	0.0495	0.3169	300	0	1052.62
	0.2294	0.05	0.0503	0.6610	298.17	8.90	408.51
	0.3333	0.1	0.0527	0.7971	203.27	43.44	193.89
	0.5	0.2	0.0505	0.8525	104.68	10.62	86.19
	1	0.5	0.0498	0.9999	100	0	21.53

Table 16: Linear regression with 10 independent continuous predictors,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0503	0.6607	293.49	26.76	384.49
	0.2294	0.05	0.0499	0.8949	242.98	73.32	149.09
	0.3333	0.1	0.0554	0.8952	157.92	83.33	70.71
	0.5	0.2	0.0611	0.8899	78.05	55.09	31.39
	1	0.5	0.0538	0.8977	25.23	12.48	7.86
50	0.1429	0.02	0.0489	0.6809	297.25	12.98	384.49
	0.2294	0.05	0.0522	0.8417	193.11	56.15	149.09
	0.3333	0.1	0.0550	0.8369	93.67	30.46	70.71
	0.5	0.2	0.0498	0.8809	52.59	6.94	31.39
	1	0.5	0.0502	0.9997	50	0	7.86
100	0.1429	0.02	0.0509	0.6746	298.82	6.92	384.49
	0.2294	0.05	0.0518	0.8155	169.91	35.98	149.09
	0.3333	0.1	0.0515	0.8800	101.55	5.65	70.71
	0.5	0.2	0.0502	0.9954	100	0	31.39
	1	0.5	0.0511	1	100	0	7.86

Table 17: Linear regression with 10 continuous predictors, Pearson correlation among the predictors = 0.4,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0483	0.5065	298.08	14.39	584.82
	0.2294	0.05	0.0498	0.8375	274.37	52.56	227.17
	0.3333	0.1	0.0526	0.9023	207.36	83.29	107.53
	0.5	0.2	0.0558	0.8914	114.66	72.23	47.72
	1	0.5	0.0612	0.8796	33.05	21.64	11.94
50	0.1429	0.02	0.0493	0.4973	299.91	2.06	584.82
	0.2294	0.05	0.0498	0.8303	261.32	47.15	227.17
	0.3333	0.1	0.0522	0.8484	141.39	45.84	107.53
	0.5	0.2	0.0531	0.8370	65.80	18.23	47.72
	1	0.5	0.0493	0.9964	50.00	0.09	11.94
100	0.1429	0.02	0.0504	0.4964	300.00	0.19	584.82
	0.2294	0.05	0.0515	0.8173	249.97	41.13	227.17
	0.3333	0.1	0.0521	0.8175	124.72	23.50	107.53
	0.5	0.2	0.0503	0.9646	100.01	0.37	47.72
	1	0.5	0.0509	1	100	0	11.94

Table 18: Linear regression with 10 continuous predictors, Pearson correlation among the predictors = 0.8,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0483	0.2104	299.96	1.89	1732.42
	0.2294	0.05	0.0502	0.4481	298.80	11.50	672.42
	0.3333	0.1	0.0494	0.7460	289.01	34.98	318.95
	0.5	0.2	0.0495	0.8891	237.71	75.33	141.67
	1	0.5	0.0603	0.8916	87.31	59.72	35.28
50	0.1429	0.02	0.0495	0.2112	300	0	1732.42
	0.2294	0.05	0.0506	0.4513	299.98	0.83	672.42
	0.3333	0.1	0.0511	0.7463	291.38	23.37	318.95
	0.5	0.2	0.0529	0.8508	184.03	55.30	141.67
	1	0.5	0.0528	0.8631	54.81	9.80	35.28
100	0.1429	0.02	0.0507	0.2063	300	0	1732.42
	0.2294	0.05	0.0489	0.4513	300	0	672.42
	0.3333	0.1	0.0519	0.7500	292.81	18.06	318.95
	0.5	0.2	0.0519	0.8185	161.66	34.23	141.67
	1	0.5	0.0509	0.9895	100.00	0.04	35.28

Table 19: Linear regression with 10 independent binary predictors,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0484	0.6678	294.66	23.91	384.37
	0.2294	0.05	0.0512	0.8905	242.58	70.45	149.15
	0.3333	0.1	0.0525	0.8953	149.99	76.24	70.65
	0.5	0.2	0.0620	0.8770	71.10	45.28	31.40
	1	0.5	0.0540	0.8944	23.59	9.60	7.85
50	0.1429	0.02	0.0486	0.6831	298.85	7.72	384.37
	0.2294	0.05	0.0561	0.8438	188.33	45.53	149.15
	0.3333	0.1	0.0529	0.8254	89.91	22.49	70.65
	0.5	0.2	0.0492	0.8842	51.10	3.66	31.40
	1	0.5	0.0501	1	50	0	7.85
100	0.1429	0.02	0.0485	0.6713	299.68	3.19	384.37
	0.2294	0.05	0.0521	0.8106	166.30	26.30	149.15
	0.3333	0.1	0.0499	0.8838	100.37	2.09	70.65
	0.5	0.2	0.0497	0.9972	100	0	31.40
	1	0.5	0.0493	1	100	0	7.85

Table 20: Linear regression with 10 binary predictors, Pairwise Pearson correlations = 0.4 (pairwise tetrachoric correlations = 0.5878),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0511	0.5035	298.73	11.56	584.24
	0.2294	0.05	0.0488	0.8453	281.09	45.89	227.21
	0.3333	0.1	0.0498	0.9230	226.07	81.83	107.63
	0.5	0.2	0.0556	0.9160	144.14	90.51	47.75
	1	0.5	0.0618	0.8952	54.28	65.52	11.93
50	0.1429	0.02	0.0492	0.4963	299.96	1.25	584.24
	0.2294	0.05	0.0497	0.8205	266.70	44.03	227.21
	0.3333	0.1	0.0524	0.8543	149.41	50.48	107.63
	0.5	0.2	0.0509	0.8381	68.91	22.27	47.75
	1	0.5	0.0492	0.9939	50.01	0.40	11.93
100	0.1429	0.02	0.0507	0.5002	300.00	0.06	584.24
	0.2294	0.05	0.0506	0.8181	253.68	39.73	227.21
	0.3333	0.1	0.0503	0.8196	126.95	24.89	107.63
	0.5	0.2	0.0494	0.9596	100.03	0.68	47.75
	1	0.5	0.0493	1	100	0	11.93

Table 21: Linear regression with 10 binary predictors, Pairwise Pearson correlations = 0.8 (pairwise tetrachoric correlations = 0.9511),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0504	0.1982	300.00	0.00	1736.86
	0.2294	0.05	0.0492	0.4207	299.94	2.59	672.07
	0.3333	0.1	0.0495	0.7181	299.67	6.53	318.79
	0.5	0.2	0.0494	0.9552	298.53	15.65	141.61
	1	0.5	0.0506	0.9978	295.87	30.41	35.47
50	0.1429	0.02	0.0515	0.1914	300	0	1736.86
	0.2294	0.05	0.0505	0.4267	299.95	1.63	672.07
	0.3333	0.1	0.0499	0.7171	295.90	18.47	318.79
	0.5	0.2	0.0515	0.9143	257.76	64.17	141.61
	1	0.5	0.0519	0.9296	149.81	104.10	35.47
100	0.1429	0.02	0.0482	0.2022	300	0	1736.86
	0.2294	0.05	0.0491	0.4212	299.99	0.66	672.07
	0.3333	0.1	0.0504	0.7177	294.09	19.19	318.79
	0.5	0.2	0.0515	0.8599	210.81	64.76	141.61
	1	0.5	0.0520	0.9529	104.06	20.08	35.47



Table 22: Linear regression with 10 independent predictors, the predictor of interest is binary, other 9 predictors are continuous,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0513	0.6604	294.81	23.66	384.37
	0.2294	0.05	0.0524	0.8961	243.06	70.45	149.15
	0.3333	0.1	0.0552	0.9009	149.92	75.88	70.65
	0.5	0.2	0.0625	0.8828	71.20	44.52	31.40
	1	0.5	0.0540	0.8936	23.47	8.81	7.85
50	0.1429	0.02	0.0501	0.6741	298.80	7.89	384.37
	0.2294	0.05	0.0503	0.8442	188.54	45.46	149.15
	0.3333	0.1	0.0541	0.8310	89.87	22.29	70.65
	0.5	0.2	0.0506	0.8753	51.08	3.60	31.40
	1	0.5	0.0503	1	50	0	7.85
100	0.1429	0.02	0.0515	0.6737	299.70	3.07	384.37
	0.2294	0.05	0.0520	0.8152	166.57	26.31	149.15
	0.3333	0.1	0.0501	0.8781	100.38	2.14	70.65
	0.5	0.2	0.0499	0.9970	100	0	31.40
	1	0.5	0.0491	1	100	0	7.85

Table 23: Linear regression with 10 predictors, the predictor of interest is binary, other 9 predictors are continuous, pairwise Pearson correlation = 0.4 (original pairwise correlation = 0.5037),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0501	0.4951	298.40	13.12	587.90
	0.2294	0.05	0.0536	0.8356	274.34	52.01	228.31
	0.3333	0.1	0.0517	0.8981	204.34	81.87	108.14
	0.5	0.2	0.0609	0.8876	108.48	66.28	48.04
	1	0.5	0.0608	0.8701	31.09	18.58	12.00
50	0.1429	0.02	0.0502	0.4999	299.96	1.26	587.90
	0.2294	0.05	0.0509	0.8266	262.08	44.58	228.31
	0.3333	0.1	0.0528	0.8416	138.44	40.61	108.14
	0.5	0.2	0.0510	0.8301	63.94	15.83	48.04
	1	0.5	0.0495	0.9974	50.00	0.04	12.00
100	0.1429	0.02	0.0500	0.4975	300.00	0.10	587.90
	0.2294	0.05	0.0523	0.8168	250.47	38.24	228.31
	0.3333	0.1	0.0521	0.8141	123.10	20.92	108.14
	0.5	0.2	0.0512	0.9613	100.00	0.20	48.04
	1	0.5	0.0492	1	100	0	12.00

Table 24: Linear regression with 10 predictors, the predictor of interest is binary, other 9 predictors are continuous, pairwise Pearson correlation = 0.72 (original pairwise correlation = 0.9),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0514	0.3108	299.83	3.93	1030.71
	0.2294	0.05	0.0483	0.6532	294.64	24.12	400.25
	0.3333	0.1	0.0514	0.8685	263.97	59.99	189.36
	0.5	0.2	0.0536	0.9017	174.57	81.95	84.07
	1	0.5	0.0662	0.8785	50.45	34.42	21.07
50	0.1429	0.02	0.0501	0.3128	300	0	1030.71
	0.2294	0.05	0.0504	0.6577	298.65	8.72	400.25
	0.3333	0.1	0.0515	0.8430	233.78	51.53	189.36
	0.5	0.2	0.0540	0.8413	108.76	31.23	84.07
	1	0.5	0.0498	0.9564	50.06	0.79	21.07
100	0.1429	0.02	0.0497	0.3193	300	0	1030.71
	0.2294	0.05	0.0492	0.6688	299.62	3.65	400.25
	0.3333	0.1	0.0514	0.8224	213.11	38.16	189.36
	0.5	0.2	0.0522	0.8425	104.82	9.50	84.07
	1	0.5	0.0510	0.9999	100	0	21.07

Table 25: Linear regression with 10 independent predictors, the predictor of interest is continuous, other 9 predictors are binary,  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0508	0.6699	293.43	27.05	384.34
	0.2294	0.05	0.0527	0.8906	242.68	73.41	149.16
	0.3333	0.1	0.0542	0.8988	158.12	83.02	70.62
	0.5	0.2	0.0614	0.8877	78.07	54.59	31.41
	1	0.5	0.0553	0.9024	25.24	12.97	7.86
50	0.1429	0.02	0.0495	0.6771	297.21	13.04	384.34
	0.2294	0.05	0.0501	0.8405	193.23	56.22	149.16
	0.3333	0.1	0.0529	0.8463	93.37	30.29	70.62
	0.5	0.2	0.0500	0.8823	52.57	6.90	31.41
	1	0.5	0.0508	0.9999	50	0	7.86
100	0.1429	0.02	0.0492	0.6793	298.86	6.76	384.34
	0.2294	0.05	0.0509	0.8174	169.88	36.04	149.16
	0.3333	0.1	0.0515	0.8780	101.56	5.64	70.62
	0.5	0.2	0.0496	0.9948	100	0	31.41
	1	0.5	0.0491	1	100	0	7.86

Table 26: Linear regression with 10 predictors, the predictor of interest is continuous, other 9 predictors are binary, pairwise Pearson correlation = 0.4 (original pairwise correlation = 0.5037),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0515	0.4985	298.19	14.05	587.73
	0.2294	0.05	0.0506	0.8325	274.60	52.62	227.98
	0.3333	0.1	0.0522	0.9054	209.27	83.73	108.06
	0.5	0.2	0.0551	0.8929	119.29	77.78	48.09
	1	0.5	0.0601	0.8769	41.13	51.65	11.99
50	0.1429	0.02	0.0506	0.5020	299.93	1.80	587.73
	0.2294	0.05	0.0508	0.8236	260.84	47.26	227.98
	0.3333	0.1	0.0515	0.8345	141.34	45.65	108.06
	0.5	0.2	0.0529	0.8371	65.78	18.34	48.09
	1	0.5	0.0505	0.9955	50.00	0.08	11.99
100	0.1429	0.02	0.0493	0.5051	300.00	0.23	587.73
	0.2294	0.05	0.0512	0.8167	250.24	41.16	227.98
	0.3333	0.1	0.0523	0.8197	124.87	23.68	108.06
	0.5	0.2	0.0512	0.9592	100.01	0.40	48.09
	1	0.5	0.0493	1	100	0	11.99

Table 27: Linear regression with 10 predictors, the predictor of interest is continuous, other 9 predictors are binary, pairwise Pearson correlation = 0.72 (original pairwise correlation = 0.9),  $N_{max} = 300$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0499	0.3237	299.98	1.30	1030.10
	0.2294	0.05	0.0512	0.6682	299.67	6.22	399.13
	0.3333	0.1	0.0507	0.9337	298.02	16.66	189.62
	0.5	0.2	0.0498	0.9935	293.74	33.59	84.09
	1	0.5	0.0506	0.9941	207.98	53.95	21.05
50	0.1429	0.02	0.0499	0.3218	300.00	0.02	1030.10
	0.2294	0.05	0.0499	0.6619	297.03	13.78	399.13
	0.3333	0.1	0.0492	0.8490	239.05	59.37	189.62
	0.5	0.2	0.0549	0.8621	139.79	79.60	84.09
	1	0.5	0.0505	0.9649	91.39	92.72	21.05
100	0.1429	0.02	0.0506	0.3247	300	0	1030.10
	0.2294	0.05	0.0509	0.6604	298.65	7.66	399.13
	0.3333	0.1	0.0487	0.8115	209.54	44.87	189.62
	0.5	0.2	0.0511	0.8545	106.26	13.99	84.09
	1	0.5	0.0491	0.9997	100.22	6.63	21.05

Table 28: Linear regression with a single continuous predictor,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0510	0.7859	410.55	142.71	385.11
	0.2294	0.05	0.0522	0.7909	176.14	87.23	149.21
	0.3333	0.1	0.0543	0.8063	83.61	42.45	70.68
	0.5	0.2	0.0551	0.8195	38.04	18.30	31.36
	1	0.5	0.0506	0.9654	20.16	1.26	7.86
50	0.1429	0.02	0.0502	0.8019	404.31	105.69	385.11
	0.2294	0.05	0.0522	0.8013	159.40	47.11	149.21
	0.3333	0.1	0.0519	0.8068	76.23	21.48	70.68
	0.5	0.2	0.0516	0.9220	50.47	2.57	31.36
	1	0.5	0.0500	1	50	0	7.86
100	0.1429	0.02	0.0510	0.8077	396.08	79.36	385.11
	0.2294	0.05	0.0511	0.8096	154.26	30.90	149.21
	0.3333	0.1	0.0512	0.9029	100.46	2.80	70.68
	0.5	0.2	0.0477	0.9970	100	0	31.36
	1	0.5	0.0502	1	100	0	7.86

Table 29: Linear regression with a single binary predictor,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0493	0.7832	399.02	120.29	385.11
	0.2294	0.05	0.0493	0.7874	158.76	54.84	149.21
	0.3333	0.1	0.0541	0.7946	75.45	26.12	70.68
	0.5	0.2	0.0577	0.7999	34.07	11.12	31.36
	1	0.5	0.0507	0.9841	20.01	0.30	7.86
50	0.1429	0.02	0.0481	0.7943	393.13	79.49	385.11
	0.2294	0.05	0.0498	0.8003	152.86	31.56	149.21
	0.3333	0.1	0.0537	0.7979	72.96	14.41	70.68
	0.5	0.2	0.0489	0.9284	50.03	0.45	31.36
	1	0.5	0.0501	1	50	0	7.86
100	0.1429	0.02	0.0497	0.8018	388.69	55.79	385.11
	0.2294	0.05	0.0494	0.7970	151.20	21.55	149.21
	0.3333	0.1	0.0489	0.9097	100.03	0.53	70.68
	0.5	0.2	0.0490	0.9988	100	0	31.36
	1	0.5	0.0507	1	100	0	7.86

Table 30: Linear regression with two independent continuous predictors,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0511	0.7971	425.13	143.08	384.58
	0.2294	0.05	0.0540	0.8062	186.48	94.79	149.03
	0.3333	0.1	0.0554	0.8051	88.43	46.16	70.69
	0.5	0.2	0.0583	0.8216	40.08	19.87	31.34
	1	0.5	0.0497	0.9576	20.25	1.70	7.86
50	0.1429	0.02	0.0498	0.7996	411.43	107.09	384.58
	0.2294	0.05	0.0526	0.8109	162.80	48.49	149.03
	0.3333	0.1	0.0522	0.8152	77.96	22.23	70.69
	0.5	0.2	0.0501	0.9167	50.60	2.97	31.34
	1	0.5	0.0510	1	50	0	7.86
100	0.1429	0.02	0.0526	0.8085	399.72	79.29	384.58
	0.2294	0.05	0.0545	0.8079	155.90	31.57	149.03
	0.3333	0.1	0.0506	0.9033	100.56	3.15	70.69
	0.5	0.2	0.0505	0.9960	100	0	31.34
	1	0.5	0.0495	1	100	0	7.86

Table 31: Linear regression with two continuous predictors, Pearson correlation between the predictors = 0.4,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0505	0.7793	471.79	134.14	457.70
	0.2294	0.05	0.0494	0.8104	221.17	109.63	177.49
	0.3333	0.1	0.0531	0.8102	105.96	55.61	84.19
	0.5	0.2	0.0559	0.8173	47.41	24.39	37.45
	1	0.5	0.0532	0.9451	20.57	2.78	9.34
50	0.1429	0.02	0.0499	0.7942	472.35	104.28	457.70
	0.2294	0.05	0.0520	0.8122	193.13	57.91	177.49
	0.3333	0.1	0.0521	0.8121	91.91	27.17	84.19
	0.5	0.2	0.0506	0.8830	51.95	5.60	37.45
	1	0.5	0.0506	0.9999	50	0	9.34
100	0.1429	0.02	0.0514	0.8074	470.18	83.33	457.70
	0.2294	0.05	0.0516	0.8076	185.41	38.42	177.49
	0.3333	0.1	0.0491	0.8557	102.99	7.86	84.19
	0.5	0.2	0.0513	0.9907	100	0	37.45
	1	0.5	0.0502	1	100	0	9.34

Table 32: Linear regression with two continuous predictors, Pearson correlation between the predictors = 0.8,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0509	0.5534	590.44	40.42	1067.68
	0.2294	0.05	0.0503	0.7912	446.91	139.74	414.85
	0.3333	0.1	0.0517	0.8068	242.66	117.20	196.10
	0.5	0.2	0.0522	0.8068	109.30	57.01	87.23
	1	0.5	0.0535	0.8392	29.29	12.71	21.79
50	0.1429	0.02	0.0521	0.5502	598.99	9.99	1067.68
	0.2294	0.05	0.0515	0.8037	437.41	107.55	414.85
	0.3333	0.1	0.0522	0.8033	213.53	63.86	196.10
	0.5	0.2	0.0517	0.8129	95.45	28.44	87.23
	1	0.5	0.0515	0.9732	50.02	0.46	21.79
100	0.1429	0.02	0.0494	0.5543	599.94	1.99	1067.68
	0.2294	0.05	0.0492	0.8053	428.91	82.76	414.85
	0.3333	0.1	0.0508	0.8051	204.99	42.03	196.10
	0.5	0.2	0.0509	0.8556	104.20	9.44	87.23
	1	0.5	0.0493	0.9997	100	0	21.79

Table 33: Linear regression with two independent binary predictors,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0512	0.7967	417.00	124.32	384.36
	0.2294	0.05	0.0516	0.8007	168.73	62.59	149.15
	0.3333	0.1	0.0540	0.8017	80.14	29.86	70.65
	0.5	0.2	0.0595	0.8030	36.26	13.12	31.40
	1	0.5	0.0506	0.9785	20.03	0.55	7.85
50	0.1429	0.02	0.0503	0.8063	401.24	82.34	384.36
	0.2294	0.05	0.0510	0.7995	156.26	32.82	149.15
	0.3333	0.1	0.0541	0.7971	74.43	15.26	70.65
	0.5	0.2	0.0508	0.9198	50.05	0.58	31.40
	1	0.5	0.0491	1	50	0	7.85
100	0.1429	0.02	0.0514	0.8066	393.08	57.08	384.36
	0.2294	0.05	0.0523	0.7935	152.89	22.01	149.15
	0.3333	0.1	0.0482	0.9058	100.04	0.65	70.65
	0.5	0.2	0.0497	0.9980	100	0	31.40
	1	0.5	0.0501	1	100	0	7.85

Table 34: Linear regression with two binary predictors, Pearson correlation between the predictors = 0.4 (tetrachoric correlation = 0.5878),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0506	0.7843	468.85	126.30	457.61
	0.2294	0.05	0.0521	0.8026	210.80	97.72	177.69
	0.3333	0.1	0.0552	0.8011	101.12	53.08	84.18
	0.5	0.2	0.0561	0.8098	45.66	28.21	37.40
	1	0.5	0.0512	0.9490	20.89	15.82	9.35
50	0.1429	0.02	0.0502	0.7947	470.98	94.03	457.61
	0.2294	0.05	0.0514	0.8076	189.06	48.73	177.69
	0.3333	0.1	0.0520	0.8020	90.03	23.23	84.18
	0.5	0.2	0.0499	0.8763	51.22	4.62	37.40
	1	0.5	0.0492	0.9999	50	0	9.35
100	0.1429	0.02	0.0503	0.8040	467.85	73.70	457.61
	0.2294	0.05	0.0511	0.8013	182.93	31.53	177.69
	0.3333	0.1	0.0513	0.8559	101.96	5.92	84.18
	0.5	0.2	0.0502	0.9927	100	0	37.40
	1	0.5	0.0502	1	100	0	9.35

Table 35: Linear regression with two binary predictors, Pearson correlation between the predictors = 0.8 (tetrachoric correlation = 0.9511),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0488	0.5356	580.94	59.14	1066.30
	0.2294	0.05	0.0494	0.7755	438.90	159.44	415.22
	0.3333	0.1	0.0516	0.8008	279.93	174.06	196.77
	0.5	0.2	0.0550	0.8075	164.96	171.06	87.35
	1	0.5	0.0537	0.8681	99.02	187.21	21.83
50	0.1429	0.02	0.0489	0.5516	596.15	21.37	1066.30
	0.2294	0.05	0.0506	0.7886	437.39	131.00	415.22
	0.3333	0.1	0.0510	0.8110	240.39	122.88	196.77
	0.5	0.2	0.0513	0.8178	112.82	76.79	87.35
	1	0.5	0.0506	0.9613	54.76	40.10	21.83
100	0.1429	0.02	0.0506	0.5543	599.43	6.79	1066.30
	0.2294	0.05	0.0510	0.7983	435.02	109.04	415.22
	0.3333	0.1	0.0509	0.8118	217.72	78.99	196.77
	0.5	0.2	0.0505	0.8623	112.13	29.27	87.35
	1	0.5	0.0506	0.9982	100.06	3.61	21.83



Table 36: Linear regression with two independent predictors (binary and continuous), the predictor of interest is binary,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0509	0.8013	416.54	125.08	384.36
	0.2294	0.05	0.0522	0.8019	168.55	62.07	149.15
	0.3333	0.1	0.0541	0.8054	80.06	29.52	70.65
	0.5	0.2	0.0594	0.8045	36.12	12.98	31.40
	1	0.5	0.0483	0.9769	20.02	0.33	7.85
50	0.1429	0.02	0.0509	0.8018	400.53	82.43	384.36
	0.2294	0.05	0.0514	0.7943	156.20	33.01	149.15
	0.3333	0.1	0.0521	0.8144	74.35	15.21	70.65
	0.5	0.2	0.0498	0.9225	50.05	0.61	31.40
	1	0.5	0.0505	1	50	0	7.85
100	0.1429	0.02	0.0514	0.7984	392.88	56.97	384.36
	0.2294	0.05	0.0526	0.8035	152.72	22.08	149.15
	0.3333	0.1	0.0513	0.9030	100.03	0.54	70.65
	0.5	0.2	0.0510	0.9977	100	0	31.40
	1	0.5	0.0513	1	100	0	7.85

Table 37: Linear regression with two predictors (binary and continuous), the predictor of interest is binary, Pearson correlation between the predictors = 0.4 (original correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0500	0.7803	467.44	124.51	458.25
	0.2294	0.05	0.0510	0.7954	204.42	85.60	177.87
	0.3333	0.1	0.0551	0.8000	96.91	40.78	84.21
	0.5	0.2	0.0590	0.8003	43.49	18.02	37.43
	1	0.5	0.0512	0.9483	20.20	1.34	9.37
50	0.1429	0.02	0.0510	0.7975	469.85	92.97	458.25
	0.2294	0.05	0.0507	0.8068	187.32	45.22	177.87
	0.3333	0.1	0.0547	0.8020	89.01	21.48	84.21
	0.5	0.2	0.0503	0.8845	50.92	3.33	37.43
	1	0.5	0.0509	1	50	0	9.37
100	0.1429	0.02	0.0494	0.7993	468.17	71.44	458.25
	0.2294	0.05	0.0507	0.7966	182.48	30.17	177.87
	0.3333	0.1	0.0493	0.8565	101.61	5.00	84.21
	0.5	0.2	0.0516	0.9947	100	0	37.43
	1	0.5	0.0501	1	100	0	9.37

Table 38: Linear regression with two predictors (binary and continuous), the predictor of interest is binary, Pearson correlation between the predictors = 0.8 (original correlation = 0.9991),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0499	0.5597	592.57	34.48	1052.06
	0.2294	0.05	0.0502	0.7986	439.55	132.44	408.97
	0.3333	0.1	0.0532	0.8059	227.40	96.76	193.72
	0.5	0.2	0.0544	0.8062	101.77	44.21	86.16
	1	0.5	0.0535	0.8262	27.27	9.64	21.54
50	0.1429	0.02	0.0508	0.5616	599.47	6.95	1052.06
	0.2294	0.05	0.0504	0.8030	429.53	96.27	408.97
	0.3333	0.1	0.0509	0.8034	206.24	52.01	193.72
	0.5	0.2	0.0540	0.7980	91.78	22.78	86.16
	1	0.5	0.0502	0.9807	50.00	0.17	21.54
100	0.1429	0.02	0.0496	0.5531	599.98	1.22	1052.06
	0.2294	0.05	0.0509	0.8003	420.95	71.04	408.97
	0.3333	0.1	0.0509	0.8046	199.91	34.65	193.72
	0.5	0.2	0.0508	0.8505	102.42	6.38	86.16
	1	0.5	0.0507	0.9999	100	0	21.54

Table 39: Linear regression with independent predictors (binary and continuous), the predictor of interest is continuous,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0499	0.7926	425.89	143.32	384.02
	0.2294	0.05	0.0519	0.8044	185.99	94.33	149.09
	0.3333	0.1	0.0544	0.8128	89.04	46.87	70.56
	0.5	0.2	0.0569	0.8174	40.33	20.26	31.34
	1	0.5	0.0495	0.9599	20.26	1.71	7.85
50	0.1429	0.02	0.0510	0.8077	411.45	107.29	384.02
	0.2294	0.05	0.0526	0.8087	162.59	48.58	149.09
	0.3333	0.1	0.0535	0.8173	77.73	22.27	70.56
	0.5	0.2	0.0521	0.9152	50.61	2.96	31.34
	1	0.5	0.0494	1	50	0	7.85
100	0.1429	0.02	0.0512	0.8056	400.12	79.69	384.02
	0.2294	0.05	0.0508	0.8029	156.00	31.58	149.09
	0.3333	0.1	0.0494	0.8996	100.52	2.93	70.56
	0.5	0.2	0.0510	0.9973	100	0	31.34
	1	0.5	0.0473	1	100	0	7.85

Table 40: Linear regression with two predictors (continuous and binary), the predictor of interest is continuous, Pearson correlation between the predictors = 0.4 (original correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0498	0.7779	473.51	133.43	458.75
	0.2294	0.05	0.0500	0.8054	221.86	110.63	178.24
	0.3333	0.1	0.0543	0.8147	105.73	55.50	84.22
	0.5	0.2	0.0578	0.8163	47.54	24.33	37.45
	1	0.5	0.0492	0.9405	20.58	2.70	9.37
50	0.1429	0.02	0.0497	0.7912	473.49	103.89	458.75
	0.2294	0.05	0.0506	0.8035	193.86	57.85	178.24
	0.3333	0.1	0.0544	0.8156	92.30	27.29	84.22
	0.5	0.2	0.0509	0.8818	52.01	5.72	37.45
	1	0.5	0.0499	0.9998	50	0	9.37
100	0.1429	0.02	0.0510	0.8016	471.30	83.59	458.75
	0.2294	0.05	0.0513	0.8095	185.78	38.04	178.24
	0.3333	0.1	0.0506	0.8584	103.07	7.94	84.22
	0.5	0.2	0.0515	0.9917	100	0	37.45
	1	0.5	0.0494	1	100	0	9.37

Table 41: Linear regression with two predictors (continuous and binary), the predictor of interest is continuous, Pearson correlation between the predictors = 0.8 (original correlation = 0.9991),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0503	0.5393	587.54	47.79	1052.62
	0.2294	0.05	0.0500	0.7845	444.78	144.96	408.51
	0.3333	0.1	0.0511	0.8112	248.33	127.12	193.89
	0.5	0.2	0.0532	0.8135	112.36	63.87	86.19
	1	0.5	0.0544	0.8454	30.35	14.85	21.53
50	0.1429	0.02	0.0503	0.5561	598.17	14.05	1052.62
	0.2294	0.05	0.0479	0.8041	435.23	113.23	408.51
	0.3333	0.1	0.0512	0.8024	214.37	70.36	193.89
	0.5	0.2	0.0527	0.8167	96.16	31.40	86.19
	1	0.5	0.0496	0.9715	50.05	0.82	21.53
100	0.1429	0.02	0.0516	0.5500	599.83	3.37	1052.62
	0.2294	0.05	0.0498	0.8056	427.37	89.19	408.51
	0.3333	0.1	0.0510	0.8036	204.12	46.11	193.89
	0.5	0.2	0.0515	0.8523	104.67	10.64	86.19
	1	0.5	0.0495	1	100	0	21.53

Table 42: Linear regression with 10 independent continuous predictors,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0484	0.8736	528.34	121.98	384.49
	0.2294	0.05	0.0514	0.9072	327.58	168.39	149.09
	0.3333	0.1	0.0527	0.8976	173.25	118.97	70.71
	0.5	0.2	0.0578	0.8867	79.36	60.32	31.39
	1	0.5	0.0562	0.8956	25.19	12.33	7.86
50	0.1429	0.02	0.0523	0.8466	472.97	109.11	384.49
	0.2294	0.05	0.0529	0.8510	197.32	65.35	149.09
	0.3333	0.1	0.0520	0.8288	93.65	30.40	70.71
	0.5	0.2	0.0515	0.8882	52.59	6.93	31.39
	1	0.5	0.0513	0.9997	50	0	7.86
100	0.1429	0.02	0.0507	0.8287	434.37	85.86	384.49
	0.2294	0.05	0.0540	0.8243	169.94	36.50	149.09
	0.3333	0.1	0.0502	0.8768	101.58	5.72	70.71
	0.5	0.2	0.0516	0.9956	100	0	31.39
	1	0.5	0.0517	1	100	0	7.86

Table 43: Linear regression with 10 continuous predictors, Pearson correlation among the predictors = 0.4,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0495	0.7802	572.13	0.91	584.82
	0.2294	0.05	0.0529	0.9077	429.29	164.76	227.17
	0.3333	0.1	0.0516	0.9082	253.38	152.89	107.53
	0.5	0.2	0.0581	0.8898	119.05	88.63	47.72
	1	0.5	0.0617	0.8777	32.99	21.82	11.94
50	0.1429	0.02	0.0495	0.7800	572.32	59.97	584.82
	0.2294	0.05	0.0511	0.8562	297.90	95.60	227.17
	0.3333	0.1	0.0535	0.8450	142.12	46.91	107.53
	0.5	0.2	0.0536	0.8332	65.92	18.54	47.72
	1	0.5	0.0493	0.9963	50.00	0.10	11.94
100	0.1429	0.02	0.0526	0.7817	573.08	49.41	584.82
	0.2294	0.05	0.0501	0.8235	258.38	55.40	227.17
	0.3333	0.1	0.0514	0.8148	124.76	23.63	107.53
	0.5	0.2	0.0503	0.9628	100.01	0.36	47.72
	1	0.5	0.0493	1	100	0	11.94

Table 44: Linear regression with 10 continuous predictors, Pearson correlation among the predictors = 0.8,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0512	0.3728	598.99	14.73	1732.42
	0.2294	0.05	0.0491	0.7231	580.66	65.67	672.42
	0.3333	0.1	0.0496	0.8916	496.99	141.12	318.95
	0.5	0.2	0.0510	0.9069	314.68	166.36	141.67
	1	0.5	0.0592	0.8886	88.91	67.60	35.28
50	0.1429	0.02	0.0495	0.3684	599.98	0.42	1732.42
	0.2294	0.05	0.0512	0.7257	587.30	40.10	672.42
	0.3333	0.1	0.0513	0.8534	408.87	113.98	318.95
	0.5	0.2	0.0523	0.8449	186.81	61.55	141.67
	1	0.5	0.0502	0.8596	54.72	9.65	35.28
100	0.1429	0.02	0.0497	0.3737	600	0	1732.42
	0.2294	0.05	0.0516	0.7388	590.78	28.75	672.42
	0.3333	0.1	0.0504	0.8199	362.12	76.39	318.95
	0.5	0.2	0.0521	0.8179	161.73	34.67	141.67
	1	0.5	0.0486	0.9901	100	0	35.28

Table 45: Linear regression with 10 independent binary predictors,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0488	0.8750	531.06	116.53	384.37
	0.2294	0.05	0.0499	0.9081	314.08	155.09	149.15
	0.3333	0.1	0.0551	0.8944	159.13	100.13	70.65
	0.5	0.2	0.0637	0.8776	71.85	41.79	31.40
	1	0.5	0.0536	0.8957	23.63	10.96	7.85
50	0.1429	0.02	0.0503	0.8524	472.04	95.59	384.37
	0.2294	0.05	0.0524	0.8462	188.96	47.64	149.15
	0.3333	0.1	0.0542	0.8319	89.70	22.42	70.65
	0.5	0.2	0.0488	0.8795	51.10	3.67	31.40
	1	0.5	0.0499	0.9999	50	0	7.85
100	0.1429	0.02	0.0520	0.8253	428.85	66.77	384.37
	0.2294	0.05	0.0516	0.8152	166.48	26.20	149.15
	0.3333	0.1	0.0489	0.8762	100.38	2.15	70.65
	0.5	0.2	0.0527	0.9973	100	0	31.40
	1	0.5	0.0512	1	100	0	7.85

Table 46: Linear regression with 10 binary predictors, Pairwise Pearson correlations = 0.4 (pairwise tetrachoric correlations = 0.5878),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0498	0.7826	579.39	68.25	584.24
	0.2294	0.05	0.0515	0.9273	463.30	159.96	227.21
	0.3333	0.1	0.0510	0.9219	309.42	182.23	107.63
	0.5	0.2	0.0555	0.9163	174.20	158.27	47.75
	1	0.5	0.0589	0.8981	68.03	121.83	11.93
50	0.1429	0.02	0.0489	0.7764	578.54	51.31	584.24
	0.2294	0.05	0.0517	0.8627	313.36	103.96	227.21
	0.3333	0.1	0.0536	0.8550	150.03	53.89	107.63
	0.5	0.2	0.0526	0.8431	68.89	22.11	47.75
	1	0.5	0.0514	0.9945	50.01	0.53	11.93
100	0.1429	0.02	0.0488	0.7766	577.12	45.08	584.24
	0.2294	0.05	0.0514	0.8228	263.98	56.73	227.21
	0.3333	0.1	0.0516	0.8184	126.83	24.71	107.63
	0.5	0.2	0.0505	0.9554	100.03	0.67	47.75
	1	0.5	0.0500	1	100	0	11.93

Table 47: Linear regression with 10 binary predictors, Pairwise Pearson correlations = 0.8 (pairwise tetrachoric correlations = 0.9511),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0499	0.3601	599.96	2.85	1736.86
	0.2294	0.05	0.0506	0.7263	599.27	14.03	672.07
	0.3333	0.1	0.0500	0.9541	597.54	28.33	318.79
	0.5	0.2	0.0483	0.9981	594.24	47.93	141.61
	1	0.5	0.0503	0.9981	589.47	72.06	35.47
50	0.1429	0.02	0.0488	0.3694	599.98	1.59	1736.86
	0.2294	0.05	0.0506	0.7201	593.12	33.73	672.07
	0.3333	0.1	0.0521	0.9191	531.88	115.56	318.79
	0.5	0.2	0.0505	0.9391	399.27	187.85	141.61
	1	0.5	0.0515	0.9291	223.57	220.59	35.47
100	0.1429	0.02	0.0492	0.3619	600	0	1736.86
	0.2294	0.05	0.0508	0.7235	591.46	31.96	672.07
	0.3333	0.1	0.0514	0.8729	454.91	124.73	318.79
	0.5	0.2	0.0521	0.8680	234.45	112.54	141.61
	1	0.5	0.0505	0.9566	104.80	28.53	35.47

Table 48: Linear regression with 10 independent predictors, the predictor of interest is binary, other 9 predictors are continuous,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0494	0.8826	531.53	116.32	384.37
	0.2294	0.05	0.0522	0.9099	313.67	155.33	149.15
	0.3333	0.1	0.0530	0.9019	158.30	97.95	70.65
	0.5	0.2	0.0630	0.8823	71.56	46.96	31.40
	1	0.5	0.0563	0.8939	23.51	8.97	7.85
50	0.1429	0.02	0.0520	0.8526	471.90	96.14	384.37
	0.2294	0.05	0.0529	0.8415	189.08	47.65	149.15
	0.3333	0.1	0.0552	0.8281	89.78	22.39	70.65
	0.5	0.2	0.0485	0.8821	51.07	3.58	31.40
	1	0.5	0.0504	1	50	0	7.85
100	0.1429	0.02	0.0505	0.8212	428.06	66.46	384.37
	0.2294	0.05	0.0509	0.8112	166.60	26.37	149.15
	0.3333	0.1	0.0496	0.8830	100.37	2.11	70.65
	0.5	0.2	0.0509	0.9971	100	0	31.40
	1	0.5	0.0489	1	100	0	7.85

Table 49: Linear regression with 10 predictors, the predictor of interest is binary, other 9 predictors are continuous, pairwise Pearson correlation = 0.4 (original pairwise correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0507	0.7801	573.16	76.29	587.90
	0.2294	0.05	0.0496	0.9034	420.60	162.25	228.31
	0.3333	0.1	0.0501	0.8996	240.03	142.39	108.14
	0.5	0.2	0.0572	0.8932	112.35	78.99	48.04
	1	0.5	0.0606	0.8726	30.87	18.65	12.00
50	0.1429	0.02	0.0505	0.7913	575.95	53.68	587.90
	0.2294	0.05	0.0533	0.8498	292.03	85.03	228.31
	0.3333	0.1	0.0528	0.8467	138.21	40.74	108.14
	0.5	0.2	0.0544	0.8337	63.88	15.81	48.04
	1	0.5	0.0497	0.9977	50.00	0.03	12.00
100	0.1429	0.02	0.0493	0.7841	577.05	43.63	587.90
	0.2294	0.05	0.0516	0.8244	255.84	48.56	228.31
	0.3333	0.1	0.0521	0.8156	123.22	20.78	108.14
	0.5	0.2	0.0490	0.9642	100.00	0.22	48.04
	1	0.5	0.0508	1	100	0	12.00

Table 50: Linear regression with 10 predictors, the predictor of interest is binary, other 9 predictors are continuous, pairwise Pearson correlation = 0.72 (original pairwise correlation = 0.9),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0509	0.5523	595.02	32.82	1030.71
	0.2294	0.05	0.0503	0.8642	534.99	115.03	400.25
	0.3333	0.1	0.0527	0.9072	379.71	164.81	189.36
	0.5	0.2	0.0551	0.9016	194.16	122.53	84.07
	1	0.5	0.0648	0.8718	50.51	34.79	21.07
50	0.1429	0.02	0.0503	0.5554	599.75	4.92	1030.71
	0.2294	0.05	0.0509	0.8446	485.32	100.09	400.25
	0.3333	0.1	0.0540	0.8500	243.47	70.03	189.36
	0.5	0.2	0.0529	0.8365	108.56	31.28	84.07
	1	0.5	0.0508	0.9585	50.07	0.88	21.07
100	0.1429	0.02	0.0504	0.5611	599.99	0.80	1030.71
	0.2294	0.05	0.0518	0.8236	447.41	77.50	400.25
	0.3333	0.1	0.0508	0.8170	213.44	39.33	189.36
	0.5	0.2	0.0519	0.8378	104.75	9.46	84.07
	1	0.5	0.0506	0.9997	100	0	21.07

Table 51: Linear regression with 10 independent predictors, the predictor of interest is continuous, other 9 predictors are binary,  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0509	0.8720	527.24	123.41	384.34
	0.2294	0.05	0.0518	0.9040	328.27	168.64	149.16
	0.3333	0.1	0.0540	0.9002	173.47	119.59	70.62
	0.5	0.2	0.0604	0.8896	79.74	61.89	31.41
	1	0.5	0.0550	0.8943	25.32	13.85	7.86
50	0.1429	0.02	0.0501	0.8489	474.01	109.31	384.34
	0.2294	0.05	0.0511	0.8448	196.78	64.94	149.16
	0.3333	0.1	0.0537	0.8409	93.55	30.65	70.62
	0.5	0.2	0.0501	0.8790	52.59	6.94	31.41
	1	0.5	0.0503	0.9997	50	0	7.86
100	0.1429	0.02	0.0527	0.8265	434.67	85.94	384.34
	0.2294	0.05	0.0503	0.8171	170.31	36.30	149.16
	0.3333	0.1	0.0511	0.8799	101.58	5.73	70.62
	0.5	0.2	0.0495	0.9963	100	0	31.41
	1	0.5	0.0496	1	100	0	7.86



Table 52: Linear regression with 10 predictors, the predictor of interest is continuous, other 9 predictors are binary, pairwise Pearson correlation = 0.4 (original pairwise correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0502	0.7753	572.42	78.53	587.73
	0.2294	0.05	0.0517	0.9037	430.10	165.92	227.98
	0.3333	0.1	0.0514	0.9049	262.79	161.82	108.06
	0.5	0.2	0.0574	0.8915	133.52	121.65	48.09
	1	0.5	0.0605	0.8758	51.28	103.57	11.99
50	0.1429	0.02	0.0516	0.7754	572.63	59.13	587.73
	0.2294	0.05	0.0504	0.8517	298.46	95.88	227.98
	0.3333	0.1	0.0516	0.8393	141.81	47.06	108.06
	0.5	0.2	0.0516	0.8411	65.72	18.33	48.09
	1	0.5	0.0517	0.9953	50.00	0.08	11.99
100	0.1429	0.02	0.0506	0.7816	573.44	48.94	587.73
	0.2294	0.05	0.0516	0.8191	259.30	55.86	227.98
	0.3333	0.1	0.0534	0.8194	125.15	23.75	108.06
	0.5	0.2	0.0515	0.9604	100.01	0.42	48.09
	1	0.5	0.0475	1	100	0	11.99

Table 53: Linear regression with 10 predictors, the predictor of interest is continuous, other 9 predictors are binary, pairwise Pearson correlation = 0.72 (original pairwise correlation = 0.9),  $N_{max} = 600$ .

n	$\beta_1$	$R^2$	Type I error	Power	$E(N)$	$SD(N)$	Target SS
20	0.1429	0.02	0.0492	0.5516	599.62	9.72	1030.10
	0.2294	0.05	0.0503	0.9150	596.37	31.70	399.13
	0.3333	0.1	0.0493	0.9932	589.05	61.72	189.62
	0.5	0.2	0.0494	0.9953	579.90	92.72	84.09
	1	0.5	0.0492	0.9919	573.76	117.32	21.05
50	0.1429	0.02	0.0493	0.5607	598.99	10.75	1030.10
	0.2294	0.05	0.0506	0.8451	492.09	114.31	399.13
	0.3333	0.1	0.0512	0.8689	300.58	154.38	189.62
	0.5	0.2	0.0531	0.8634	189.49	186.64	84.09
	1	0.5	0.0513	0.9637	139.77	203.07	21.05
100	0.1429	0.02	0.0495	0.5593	599.87	3.05	1030.10
	0.2294	0.05	0.0508	0.8231	440.37	90.82	399.13
	0.3333	0.1	0.0526	0.8173	211.45	49.89	189.62
	0.5	0.2	0.0506	0.8454	106.63	19.72	84.09
	1	0.5	0.0509	0.9998	100.49	15.64	21.05

Table 54: Logistic regression with a single continuous predictor,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0488	0.8644	478.90	114.14	0.0224	0.0130	392.36
	0.469	0.0457	0.8660	214.96	101.14	0.0524	0.0285	166.54
	0.702	0.0391	0.8554	98.83	57.40	0.1001	0.0488	86.83
	1.127	0.0292	0.8439	39.21	26.90	0.1891	0.0791	47.90
50	0.291	0.0490	0.8308	425.29	87.56	0.0219	0.0132	392.36
	0.469	0.0446	0.8363	166.38	39.80	0.0521	0.0288	166.54
	0.702	0.0384	0.8161	74.41	17.41	0.0990	0.0514	86.83
	1.127	0.0421	0.9176	50.07	0.95	0.1946	0.0782	47.90
100	0.291	0.0467	0.8133	398.50	60.38	0.0221	0.0135	392.36
	0.469	0.0448	0.8021	153.97	23.63	0.0516	0.0300	166.54
	0.702	0.0473	0.9061	100.05	0.89	0.1039	0.0500	86.83
	1.127	0.0444	0.9984	100	0	0.2057	0.0656	47.90

Table 55: Logistic regression with a single binary predictor,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0499	0.8545	459.82	63.38	0.0218	0.0131	391.74
	0.459	0.0469	0.8548	188.42	59.70	0.0528	0.0300	157.01
	0.667	0.0465	0.8566	93.59	59.72	0.1024	0.0545	78.72
	1.003	0.0370	0.8365	45.18	60.91	0.1900	0.0881	39.74
50	0.286	0.0497	0.8244	411.33	26.50	0.0223	0.0138	391.74
	0.459	0.0477	0.8267	160.18	11.36	0.0541	0.0316	157.01
	0.667	0.0446	0.8186	76.11	5.42	0.1032	0.0570	78.72
	1.003	0.0471	0.9222	50.02	2.50	0.2033	0.0877	39.74
100	0.286	0.0486	0.8104	396.69	10.95	0.0221	0.0139	391.74
	0.459	0.0495	0.8094	154.33	4.29	0.0541	0.0326	157.01
	0.667	0.0520	0.9076	100.00	0.04	0.1066	0.0552	78.72
	1.003	0.0516	0.9974	100	0	0.2043	0.0707	39.74

Table 56: Logistic regression with two independent continuous predictors,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0492	0.8807	508.73	106.29	0.0237	0.0127	396.85
	0.469	0.0459	0.9013	248.82	119.86	0.0558	0.0264	166.12
	0.702	0.0422	0.8859	116.55	76.50	0.1067	0.0464	86.69
	1.127	0.0319	0.8756	46.62	40.16	0.2016	0.0727	47.49
50	0.291	0.0464	0.8443	442.11	89.96	0.0241	0.0133	396.85
	0.469	0.0447	0.8386	173.53	42.43	0.0570	0.0297	166.12
	0.702	0.0388	0.8274	78.05	19.09	0.1084	0.0511	86.69
	1.127	0.0427	0.9237	50.13	1.52	0.2079	0.0747	47.49
100	0.291	0.0493	0.8245	407.12	61.93	0.0244	0.0136	396.85
	0.469	0.0435	0.8176	157.11	24.23	0.0563	0.0304	166.12
	0.702	0.0479	0.8974	100.08	1.09	0.1106	0.0503	86.69
	1.127	0.0471	0.9981	100	0	0.2153	0.0666	47.49

Table 57: Logistic regression with two continuous predictors, Pearson correlation between the predictors = 0.4,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0480	0.8557	547.81	82.76	0.0237	0.0123	464.24
	0.469	0.0477	0.8981	289.54	126.37	0.0550	0.0248	194.38
	0.702	0.0428	0.8863	136.58	83.34	0.1061	0.0437	100.99
	1.127	0.0348	0.8803	55.32	45.66	0.2017	0.0695	54.01
50	0.291	0.0494	0.8341	508.49	81.13	0.0239	0.0125	464.24
	0.469	0.0464	0.8355	206.83	50.21	0.0559	0.0275	194.38
	0.702	0.0419	0.8307	92.76	22.70	0.1076	0.0482	100.99
	1.127	0.0408	0.8772	50.51	2.97	0.2061	0.0746	54.01
100	0.291	0.0466	0.8262	481.18	66.65	0.0240	0.0127	464.24
	0.469	0.0435	0.8208	186.77	28.82	0.0564	0.0274	194.38
	0.702	0.0454	0.8474	100.95	3.94	0.1087	0.0479	100.99
	1.127	0.0460	0.9945	100	0	0.2128	0.0646	54.01

Table 58: Logistic regression with two continuous predictors, Pearson correlation between the predictors = 0.8,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0498	0.5715	599.88	3.46	0.0237	0.0117	1062.13
	0.469	0.0471	0.8734	525.05	97.51	0.0532	0.0185	433.57
	0.702	0.0487	0.8924	300.21	129.10	0.1030	0.0313	213.53
	1.127	0.0406	0.8922	124.32	78.21	0.2022	0.0536	103.81
50	0.291	0.0493	0.5533	600.00	0.3191	0.0235	0.0117	1062.13
	0.469	0.0475	0.8321	469.13	88.06	0.0529	0.0192	433.57
	0.702	0.0468	0.8449	215.08	52.58	0.1044	0.0349	213.53
	1.127	0.0397	0.8351	83.98	20.72	0.2040	0.0592	103.81
100	0.291	0.0483	0.5522	600	0	0.0234	0.0118	1062.13
	0.469	0.0485	0.8262	434.66	64.92	0.0532	0.0195	433.57
	0.702	0.0469	0.8203	194.63	30.11	0.1043	0.0352	213.53
	1.127	0.0470	0.8533	100.26	2.00	0.2059	0.0587	103.81

Table 59: Logistic regression with two independent binary predictors,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0493	0.8905	507.22	67.53	0.0238	0.0127	391.75
	0.459	0.0489	0.8930	214.95	67.46	0.0571	0.0290	157.01
	0.667	0.0477	0.8888	106.20	60.97	0.1098	0.0515	78.71
	1.003	0.0418	0.8782	51.19	61.59	0.2060	0.0844	39.74
50	0.286	0.0497	0.8321	431.31	35.73	0.0242	0.0138	391.75
	0.459	0.0500	0.8355	168.08	15.76	0.0583	0.0315	157.01
	0.667	0.0454	0.8272	79.79	7.44	0.1127	0.0561	78.71
	1.003	0.0490	0.9161	50.04	0.85	0.2163	0.0862	39.74
100	0.286	0.0506	0.8157	405.52	14.85	0.0243	0.0139	391.75
	0.459	0.0483	0.8144	157.76	5.81	0.0601	0.0333	157.01
	0.667	0.0501	0.9092	100.00	0.03	0.1162	0.0557	78.71
	1.003	0.0526	0.9982	100	0	0.2122	0.0702	39.74

Table 60: Logistic regression with two binary predictors, Pearson correlation between the predictors = 0.4 (tetrachoric correlation = 0.5878),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0479	0.8546	544.52	64.15	0.0236	0.0125	465.48
	0.459	0.0502	0.8858	251.90	83.06	0.0564	0.0269	186.83
	0.667	0.0461	0.8806	123.85	66.24	0.1101	0.0497	93.79
	1.003	0.0416	0.8629	59.81	66.09	0.2075	0.0813	47.28
50	0.286	0.0490	0.8379	513.44	61.26	0.0238	0.0125	465.48
	0.459	0.0480	0.8412	209.22	49.24	0.0574	0.0289	186.83
	0.667	0.0440	0.8320	99.36	23.17	0.1099	0.0521	93.79
	1.003	0.0413	0.8649	51.78	6.87	0.2105	0.0837	47.28
100	0.286	0.0488	0.8268	489.12	48.26	0.0240	0.0128	465.48
	0.459	0.0470	0.8160	191.14	21.86	0.0592	0.0302	186.83
	0.667	0.0465	0.8478	101.45	5.36	0.1122	0.0522	93.79
	1.003	0.0500	0.9923	100.00	0.03	0.2125	0.0703	47.28

Table 61: Logistic regression with two binary predictors, Pearson correlation between the predictors = 0.8 (tetrachoric correlation = 0.9511),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0484	0.5017	533.25	81.80	0.0239	0.0126	1073.74
	0.459	0.0438	0.6379	317.01	154.72	0.0568	0.0261	437.37
	0.667	0.0311	0.6210	192.22	167.95	0.1099	0.0478	218.31
	1.003	0.0129	0.5397	130.27	185.98	0.2115	0.0768	111.50
50	0.286	0.0465	0.5285	572.79	66.80	0.0235	0.0120	1073.74
	0.459	0.0480	0.7701	431.22	155.40	0.0555	0.0234	437.37
	0.667	0.0341	0.7414	226.80	106.71	0.1106	0.0435	218.31
	1.003	0.0201	0.6117	104.75	55.37	0.2188	0.0729	111.50
100	0.286	0.0494	0.5407	597.69	21.47	0.0231	0.0117	1073.74
	0.459	0.0470	0.8160	466.91	108.22	0.0541	0.0208	437.37
	0.667	0.0370	0.8070	247.41	102.48	0.1071	0.0389	218.31
	1.003	0.0281	0.7997	120.64	39.65	0.2087	0.0625	111.50

Table 62: Logistic regression with two independent predictors (binary and continuous), the predictor of interest is binary,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0494	0.8866	509.00	68.09	0.0235	0.0126	391.74
	0.459	0.0489	0.8957	219.25	78.61	0.0569	0.0286	157.01
	0.667	0.0474	0.8908	108.95	67.96	0.1091	0.0508	78.71
	1.003	0.0419	0.8812	52.84	65.30	0.2037	0.0807	39.74
50	0.286	0.0509	0.8383	430.88	35.14	0.0240	0.0136	391.74
	0.459	0.0490	0.8350	167.59	14.77	0.0582	0.0313	157.01
	0.667	0.0457	0.8331	79.66	6.97	0.1130	0.0558	78.71
	1.003	0.0502	0.9190	50.03	0.59	0.2137	0.0838	39.74
100	0.286	0.0490	0.8203	405.28	14.65	0.0245	0.0139	391.74
	0.459	0.0489	0.8131	157.69	5.69	0.0596	0.0327	157.01
	0.667	0.0505	0.9093	100.00	0.01	0.1162	0.0557	78.71
	1.003	0.0502	0.9981	100	0	0.2116	0.0698	39.74

Table 63: Logistic regression with two predictors (binary and continuous), the predictor of interest is binary, Pearson correlation between the predictors = 0.4 (original correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0489	0.8648	554.50	58.52	0.0235	0.0121	467.00
	0.459	0.0476	0.8910	264.90	98.79	0.0561	0.0264	187.54
	0.667	0.0462	0.8834	132.19	78.02	0.1077	0.0473	93.60
	1.003	0.0409	0.8780	63.41	67.92	0.2028	0.0775	47.51
50	0.286	0.0494	0.8365	511.07	56.89	0.0235	0.0125	467.00
	0.459	0.0470	0.8301	202.87	31.56	0.0571	0.0291	187.54
	0.667	0.0447	0.8318	96.11	14.78	0.1114	0.0525	93.60
	1.003	0.0438	0.8675	50.69	3.84	0.2097	0.0925	47.51
100	0.286	0.0491	0.8221	485.62	42.02	0.0238	0.0127	467.00
	0.459	0.0480	0.8114	189.05	16.93	0.0580	0.0297	187.54
	0.667	0.0479	0.8436	100.63	2.66	0.1125	0.0534	93.60
	1.003	0.0491	0.9914	100	0	0.2126	0.0702	47.51

Table 64: Logistic regression with two predictors (binary and continuous), the predictor of interest is binary, Pearson correlation between the predictors = 0.8 (original correlation = 0.9991),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0507	0.5537	600.00	0.65	0.0231	0.0116	1073.74
	0.459	0.0509	0.8695	531.41	80.69	0.0535	0.0185	428.96
	0.667	0.0480	0.8919	298.50	108.22	0.1036	0.0321	215.89
	1.003	0.0454	0.8892	141.19	84.00	0.2023	0.0537	108.67
50	0.286	0.0514	0.5563	600	0	0.0233	0.0117	1073.74
	0.459	0.0488	0.8401	469.82	67.86	0.0534	0.0193	428.96
	0.667	0.0488	0.8317	224.60	37.77	0.1053	0.0354	215.89
	1.003	0.0436	0.8322	99.65	16.88	0.2037	0.0607	108.67
100	0.286	0.0486	0.5549	600	0	0.0234	0.0117	1073.74
	0.459	0.0489	0.8161	438.70	45.18	0.0533	0.0198	428.96
	0.667	0.0464	0.8219	207.97	21.56	0.1055	0.0369	215.89
	1.003	0.0487	0.8150	101.32	3.87	0.2051	0.0622	108.67

Table 65: Logistic regression with independent predictors (binary and continuous), the predictor of interest is continuous,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0485	0.8846	509.75	105.03	0.0240	0.0130	392.44
	0.469	0.0483	0.8912	247.08	118.34	0.0554	0.0269	165.90
	0.702	0.0421	0.8888	115.87	75.07	0.1076	0.0467	86.91
	1.127	0.0318	0.8806	46.27	39.26	0.2019	0.0728	47.37
50	0.291	0.0480	0.8472	442.24	89.75	0.0243	0.0134	392.44
	0.469	0.0455	0.8400	173.85	42.78	0.0568	0.0297	165.90
	0.702	0.0402	0.8297	78.03	19.05	0.1073	0.0506	86.91
	1.127	0.0420	0.9181	50.13	1.59	0.2070	0.0752	47.37
100	0.291	0.0469	0.8187	407.13	61.71	0.0242	0.0135	392.44
	0.469	0.0440	0.8111	157.13	24.43	0.0570	0.0296	165.90
	0.702	0.0474	0.8992	100.08	1.11	0.1119	0.0506	86.91
	1.127	0.0482	0.9985	100	0	0.2135	0.0671	47.37

Table 66: Logistic regression with two predictors (continuous and binary), the predictor of interest is continuous, Pearson correlation between the predictors = 0.4 (original correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0478	0.8605	547.89	82.85	0.0237	0.0123	467.64
	0.469	0.0468	0.8987	290.81	127.43	0.0551	0.0253	194.36
	0.702	0.0437	0.8894	137.09	83.32	0.1059	0.0433	101.54
	1.127	0.0334	0.8747	55.38	45.61	0.2025	0.0710	54.04
50	0.291	0.0504	0.8316	508.91	81.19	0.0238	0.0126	467.64
	0.469	0.0460	0.8419	207.00	50.76	0.0559	0.0269	194.36
	0.702	0.0416	0.8331	92.87	22.91	0.1074	0.0474	101.54
	1.127	0.0410	0.8774	50.50	2.85	0.2056	0.0743	54.04
100	0.291	0.0480	0.8181	481.96	67.03	0.0238	0.0126	467.64
	0.469	0.0460	0.8248	187.54	29.11	0.0566	0.0279	194.36
	0.702	0.0449	0.8478	100.96	3.98	0.1091	0.0480	101.54
	1.127	0.0459	0.9932	100	0	0.2122	0.0659	54.04

Table 67: Logistic regression with two predictors (continuous and binary), the predictor of interest is continuous, Pearson correlation between the predictors = 0.8 (original correlation = 0.9991),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0507	0.5539	599.52	7.19	0.0235	0.0117	1084.87
	0.469	0.0500	0.8590	523.37	104.62	0.0531	0.0183	451.97
	0.702	0.0459	0.8881	311.91	140.72	0.1028	0.0306	237.06
	1.127	0.0412	0.8751	132.03	89.97	0.2028	0.0488	129.16
50	0.291	0.0494	0.5523	599.95	1.65	0.0236	0.0117	1084.87
	0.469	0.0504	0.8285	469.61	97.07	0.0524	0.0187	451.97
	0.702	0.0441	0.8338	219.58	63.28	0.1037	0.0328	237.06
	1.127	0.0396	0.8262	85.55	24.40	0.2018	0.0532	129.16
100	0.291	0.0496	0.5517	600.00	0.34	0.0235	0.0117	1084.87
	0.469	0.0476	0.8180	434.85	74.89	0.0530	0.0191	451.97
	0.702	0.0440	0.8150	195.57	36.02	0.1038	0.0339	237.06
	1.127	0.0448	0.8217	100.52	3.06	0.2016	0.0543	129.16



Table 68: Logistic regression with 10 independent continuous predictors,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0522	0.9408	597.34	19.76	0.0368	0.0133	394.94
	0.469	0.0515	0.9943	532.33	115.92	0.0679	0.0209	166.74
	0.702	0.0506	0.9921	394.69	183.77	0.1239	0.0339	87.00
	1.127	0.0510	0.9892	234.16	193.66	0.2363	0.0557	47.75
50	0.291	0.0499	0.9211	564.08	60.60	0.0374	0.0137	394.94
	0.469	0.0498	0.9403	271.46	89.95	0.0803	0.0269	166.74
	0.702	0.0482	0.9337	123.13	47.71	0.1492	0.0434	87.00
	1.127	0.0480	0.9378	55.49	16.02	0.2630	0.0574	47.75
100	0.291	0.0493	0.8740	482.99	71.47	0.0395	0.0146	394.94
	0.469	0.0506	0.8733	188.30	32.49	0.0909	0.0299	166.74
	0.702	0.0559	0.9011	101.39	5.15	0.1685	0.0472	87.00
	1.127	0.0563	0.9968	100	0	0.2747	0.0638	47.75

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Table 69: Logistic regression with 10 continuous predictors, Pearson correlation among the predictors = 0.4,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0492	0.8176	599.78	5.04	0.0368	0.0131	593.26
	0.469	0.0509	0.9870	573.48	70.97	0.0661	0.0190	243.22
	0.702	0.0516	0.9901	466.23	158.65	0.1198	0.0291	124.41
	1.127	0.0517	0.9868	292.68	196.01	0.2305	0.0481	64.02
50	0.291	0.0512	0.8095	598.96	8.80	0.0367	0.0133	593.26
	0.469	0.0485	0.9448	401.22	107.13	0.0714	0.0222	243.22
	0.702	0.0504	0.9376	185.60	66.53	0.1356	0.0373	124.41
	1.127	0.0475	0.9331	73.49	28.45	0.2497	0.0537	64.02
100	0.291	0.0508	0.8074	595.50	16.66	0.0368	0.0132	593.26
	0.469	0.0504	0.8793	286.08	49.66	0.0780	0.0250	243.22
	0.702	0.0490	0.8717	128.50	21.30	0.1497	0.0412	124.41
	1.127	0.0562	0.9745	100.00	0.15	0.2694	0.0590	64.02

Table 70: Logistic regression with 10 continuous predictors, Pearson correlation among the predictors = 0.8,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0532	0.3741	600	0	0.0366	0.0133	1716.16
	0.469	0.0509	0.7452	599.89	4.02	0.0654	0.0182	688.07
	0.702	0.0512	0.9640	589.21	43.72	0.1150	0.0237	337.57
	1.127	0.0520	0.9892	487.98	147.31	0.2170	0.0327	156.66
50	0.291	0.0524	0.3880	600	0	0.0365	0.0132	1716.16
	0.469	0.0526	0.7318	599.82	3.44	0.0654	0.0183	688.07
	0.702	0.0488	0.9383	497.14	95.00	0.1163	0.0244	337.57
	1.127	0.0491	0.9479	213.27	74.93	0.2231	0.0379	156.66
100	0.291	0.0525	0.3851	600	0	0.0367	0.0133	1716.16
	0.469	0.0494	0.7506	599.45	5.37	0.0655	0.0179	688.07
	0.702	0.0493	0.8773	378.02	64.81	0.1192	0.0265	337.57
	1.127	0.0501	0.8719	147.23	25.34	0.2334	0.0444	156.66

Table 71: Logistic regression with 10 independent binary predictors,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0511	0.9369	599.62	5.18	0.0363	0.0132	391.79
	0.459	0.0506	0.9950	515.07	112.61	0.0694	0.0213	157.02
	0.667	0.0554	0.9940	333.89	157.14	0.1310	0.0381	78.72
	1.003	0.0563	0.9917	174.35	130.49	0.2553	0.0686	39.74
50	0.286	0.0539	0.9263	581.64	32.53	0.0366	0.0134	391.79
	0.459	0.0509	0.9469	266.10	66.11	0.0821	0.0276	157.02
	0.667	0.0535	0.9419	126.84	36.04	0.1532	0.0447	78.72
	1.003	0.0511	0.9282	58.25	16.43	0.2669	0.0616	39.74
100	0.286	0.0507	0.8814	487.17	38.04	0.0395	0.0145	391.79
	0.459	0.0536	0.8700	189.67	15.54	0.0940	0.0313	157.02
	0.667	0.0573	0.8922	100.58	2.65	0.1757	0.0508	78.72
	1.003	0.0596	0.9958	100	0	0.2771	0.0701	39.74

Table 72: Logistic regression with 10 binary predictors, Pairwise Pearson correlations = 0.4 (pairwise tetrachoric correlations = 0.5878),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0530	0.8097	599.85	3.28	0.0364	0.0131	593.40
	0.459	0.0540	0.9829	546.10	90.59	0.0681	0.0205	237.59
	0.667	0.0536	0.9835	366.61	150.23	0.1302	0.0370	120.56
	1.003	0.0574	0.9689	196.80	140.95	0.2570	0.0698	60.46
50	0.286	0.0514	0.7985	599.83	2.81	0.0361	0.0132	593.40
	0.459	0.0513	0.9595	453.58	113.56	0.0702	0.0213	237.59
	0.667	0.0510	0.9576	242.70	107.94	0.1315	0.0369	120.56
	1.003	0.0472	0.9563	110.43	60.86	0.2454	0.0561	60.46
100	0.286	0.0503	0.8017	598.89	7.11	0.0362	0.0133	593.40
	0.459	0.0503	0.8920	314.40	61.30	0.0776	0.0250	237.59
	0.667	0.0497	0.8902	149.46	30.09	0.1473	0.0425	120.56
	1.003	0.0588	0.9634	100.31	3.27	0.2645	0.0621	60.46

Table 73: Logistic regression with 10 binary predictors, Pairwise Pearson correlations = 0.8 (pairwise tetrachoric correlations = 0.9511),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0525	0.3753	599.98	1.84	0.0366	0.0134	1762.09
	0.459	0.0514	0.7320	598.22	18.84	0.0663	0.0186	712.72
	0.667	0.0510	0.9520	593.21	47.99	0.1156	0.0246	354.25
	1.003	0.0523	0.9884	589.54	69.44	0.2151	0.0334	177.01
50	0.286	0.0528	0.3734	599.92	3.82	0.0370	0.0135	1762.09
	0.459	0.0532	0.7393	598.74	15.46	0.0663	0.0187	712.72
	0.667	0.0523	0.9357	556.26	83.04	0.1180	0.0281	354.25
	1.003	0.0543	0.9000	378.26	161.75	0.2323	0.0510	177.01
100	0.286	0.0532	0.3695	600	0	0.0365	0.0133	1762.09
	0.459	0.0535	0.7388	599.54	6.45	0.0661	0.0185	712.72
	0.667	0.0522	0.9367	556.67	80.80	0.1158	0.0247	354.25
	1.003	0.0468	0.9658	375.98	153.40	0.2199	0.0374	177.01

Table 74: Logistic regression with 10 independent predictors, the predictor of interest is binary, other 9 predictors are continuous,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0520	0.9350	599.69	4.51	0.0365	0.0132	391.77
	0.459	0.0518	0.9963	534.27	105.22	0.0680	0.0202	157.01
	0.667	0.0523	0.9964	393.54	175.21	0.1254	0.0350	78.71
	1.003	0.0536	0.9941	250.82	191.27	0.2378	0.0572	39.74
50	0.286	0.0510	0.9274	581.53	32.61	0.0367	0.0133	391.77
	0.459	0.0535	0.9486	265.32	65.28	0.0821	0.0274	157.01
	0.667	0.0533	0.9361	126.53	35.85	0.1515	0.0446	78.71
	1.003	0.0501	0.9291	58.00	16.12	0.2687	0.0613	39.74
100	0.286	0.0505	0.8785	486.64	37.52	0.0396	0.0144	391.77
	0.459	0.0540	0.8682	189.63	15.45	0.0939	0.0318	157.01
	0.667	0.0572	0.8911	100.53	2.49	0.1758	0.0506	78.71
	1.003	0.0590	0.9970	100	0	0.2783	0.0701	39.74

Table 75: Logistic regression with 10 predictors, the predictor of interest is binary, other 9 predictors are continuous, pairwise Pearson correlation = 0.4 (original pairwise correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0492	0.7925	599.97	1.47	0.0363	0.0136	597.42
	0.459	0.0501	0.9901	575.61	63.98	0.0670	0.0194	240.41
	0.667	0.0507	0.9927	471.43	151.70	0.1207	0.0301	120.93
	1.003	0.0505	0.9917	319.03	193.86	0.2294	0.0496	60.78
50	0.286	0.0518	0.8005	599.89	2.22	0.0363	0.0133	597.42
	0.459	0.0508	0.9396	403.79	96.17	0.0721	0.0221	240.41
	0.667	0.0511	0.9383	196.77	61.94	0.1363	0.0391	120.93
	1.003	0.0489	0.9378	87.88	30.87	0.2494	0.0564	60.78
100	0.286	0.0521	0.8081	599.15	5.70	0.0364	0.0132	597.42
	0.459	0.0504	0.8741	292.75	40.37	0.0794	0.0258	240.41
	0.667	0.0493	0.8667	138.82	18.99	0.1520	0.0437	120.93
	1.003	0.0582	0.9620	100.01	0.27	0.2713	0.0643	60.78

Table 76: Logistic regression with 10 predictors, the predictor of interest is binary, other 9 predictors are continuous, pairwise Pearson correlation = 0.72 (original pairwise correlation = 0.9),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.286	0.0511	0.5629	600	0	0.0364	0.0132	1049.87
	0.459	0.0512	0.9167	598.97	10.98	0.0656	0.0184	420.83
	0.667	0.0516	0.9914	563.34	80.93	0.1163	0.0253	211.10
	1.003	0.0525	0.9900	431.60	168.27	0.2190	0.0374	106.01
50	0.286	0.0516	0.5584	600	0	0.0364	0.0133	1049.87
	0.459	0.0519	0.9085	581.73	38.50	0.0662	0.0187	420.83
	0.667	0.0513	0.9484	343.14	89.02	0.1218	0.0295	211.10
	1.003	0.0508	0.9451	154.28	48.83	0.2307	0.0465	106.01
100	0.286	0.0529	0.5651	600	0	0.0363	0.0132	1049.87
	0.459	0.0527	0.8753	510.27	56.14	0.0672	0.0194	420.83
	0.667	0.0498	0.8719	244.29	31.44	0.1301	0.0338	211.10
	1.003	0.0519	0.8684	110.24	11.85	0.2467	0.0528	106.01

Table 77: Logistic regression with 10 independent predictors, the predictor of interest is continuous, other 9 predictors are binary,  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0520	0.9401	597.79	17.65	0.0369	0.0134	378.70
	0.469	0.0510	0.9954	536.70	112.53	0.0677	0.0204	150.73
	0.702	0.0500	0.9943	404.40	184.56	0.1239	0.0331	71.90
	1.127	0.0506	0.9906	249.71	210.36	0.2350	0.0536	33.44
50	0.291	0.0512	0.9219	564.69	60.05	0.0373	0.0136	378.70
	0.469	0.0497	0.9411	272.22	90.32	0.0800	0.0268	150.73
	0.702	0.0483	0.9316	122.82	46.71	0.1485	0.0438	71.90
	1.127	0.0498	0.9365	55.63	16.49	0.2628	0.0577	33.44
100	0.291	0.0508	0.8797	482.27	71.47	0.0396	0.0146	378.70
	0.469	0.0488	0.8720	188.39	32.54	0.0912	0.0299	150.73
	0.702	0.0541	0.8966	101.43	5.29	0.1674	0.0467	71.90
	1.127	0.0572	0.9978	100.00	0.01	0.2737	0.0628	33.44

Table 78: Logistic regression with 10 predictors, the predictor of interest is continuous, other 9 predictors are binary, pairwise Pearson correlation = 0.4 (original pairwise correlation = 0.5037),  $N_{max} = 600$ .

n	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0516	0.8112	599.88	3.61	0.0368	0.0132	510.82
	0.469	0.0529	0.9920	580.43	61.30	0.0657	0.0186	203.06
	0.702	0.0522	0.9940	492.54	149.35	0.1187	0.0283	97.02
	1.127	0.0508	0.9920	336.80	205.43	0.2279	0.0456	44.98
50	0.291	0.0510	0.8070	598.76	9.84	0.0366	0.0132	510.82
	0.469	0.0508	0.9415	398.41	108.03	0.0713	0.0219	203.06
	0.702	0.0489	0.9391	185.10	67.78	0.1350	0.0369	97.02
	1.127	0.0466	0.9324	73.15	28.42	0.2500	0.0544	44.98
100	0.291	0.0496	0.7993	595.18	17.50	0.0368	0.0133	510.82
	0.469	0.0502	0.8702	285.96	49.59	0.0783	0.0248	203.06
	0.702	0.0489	0.8682	128.52	21.51	0.1499	0.0411	97.02
	1.127	0.0568	0.9715	100.00	0.41	0.2697	0.0589	44.98

Table 79: Logistic regression with 10 predictors, the predictor of interest is continuous, other 9 predictors are binary, pairwise Pearson correlation = 0.72 (original pairwise correlation = 0.9),  $N_{max} = 600$ .

$n$	$\beta_1$	Type I error	Power	$E(N)$	$SD(N)$	$E(R^2)$	$SD(R^2)$	Target SS
20	0.291	0.0497	0.5681	600.00	0.01	0.0370	0.0135	825.22
	0.469	0.0483	0.9130	599.56	8.98	0.0657	0.0185	326.66
	0.702	0.0510	0.9977	595.56	34.58	0.1150	0.0235	155.84
	1.127	0.0502	0.9988	585.79	74.43	0.2146	0.0291	72.23
50	0.291	0.0497	0.5637	599.99	0.78	0.0369	0.0133	825.22
	0.469	0.0508	0.8888	545.41	78.83	0.0669	0.0189	326.66
	0.702	0.0480	0.9155	330.44	145.61	0.1240	0.0301	155.84
	1.127	0.0437	0.9094	189.60	186.09	0.2376	0.0475	72.23
100	0.291	0.0486	0.5615	600	0	0.0368	0.0133	825.22
	0.469	0.0477	0.8555	475.59	77.85	0.0683	0.0194	326.66
	0.702	0.0455	0.8515	215.75	43.41	0.1309	0.0326	155.84
	1.127	0.0485	0.8361	102.35	17.92	0.2515	0.0501	72.23

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