Is it time to rethink pre-post randomised controlled trials in strength and conditioning? A review of statistical approaches with derivations and simulations.

Paul, A. Swinton

Doi: 10.51224/SRXIV.363
SportRχiv hosted preprint version 1
28/12/2023
PREPRINT - NOT PEER REVIEWED

Contact details

Dr. Paul Swinton

School of Health Sciences, Robert Gordon University

Garthdee Road

Aberdeen, UK,

AB10 7QG

p.swinton@rgu.ac.uk, +44 (0) 1224 262 3361

Twitter Handle:
@PaulSwinton9

Please cite as: Swinton, PA. Is it time to rethink pre-post randomised controlled trials in strength and conditioning? A review of statistical approaches with derivations and simulations. 2023. Pre-print available from SportRχiv. https://doi.org/10.51224/SRXIV.363.

Abstract

Randomised controlled trials (RCTs) featuring a single measurement at baseline and post-intervention is the most common study type used to build an evidence base in strength and conditioning. The purpose of this simulation study with mathematical derivations was to explore the accuracy of inferences made with this design and the factors that may increase the proportion of Type I and Type II errors.

Realistic pre-post RCT data were simulated for strength and conditioning interventions based on parameters obtained from recent large meta-analyses. A total of nine outcomes from three domains (strength, power, and speed) were simulated whilst adjusting for a range of factors including sample size (N=10,15,25, and 50), the average treatment effect (ATE), the relationship between baseline and change scores, the amount of baseline imbalance, and measurement error. Four categories of ATE were used including zero, to investigate proportion of Type I errors, and small, medium and large ATEs to investigate proportion of Type II errors. Monte-Carlo simulation with 10,000 iterations were performed for each scenario using three different statistical tests including ANOVA, T-test on post-intervention values, and ANCOVA.

Proportion of Type I errors were close to 5% when testing a single outcome and increased to ~10-13% when testing three outcomes, and ~20-30% when testing nine outcomes. ANCOVA was shown to be the most precise statistical test with increased precision obtained with baseline imbalance and relationships between baseline and change scores. Sample size, ATE and measurement error were shown to be the most relevant factors controlling Type II errors. In the worst-case scenario (e.g., N=10, small ATE and large measurement error) statistical power was likely to be ~0.1. Even with sample sizes of 50, statistical power was unlikely to exceed 0.4 when combined with small ATE and large measurement error.

The results of this study show that sample sizes and ATE commonly investigated in strength and conditioning are likely to lead to a high proportion of inferential errors. More novel study designs and analysis approaches are required to account for these statistical challenges whilst adhering to the resource constraints that typically exist within the discipline.

Introduction

Research in strength and conditioning plays an integral role in developing evidence-based practice and thereby the physical performance of athletes. In many cases, training practices are developed and reproduced by athletes and coaches based on trial and error and building of anecdotal support. Empirical research is then conducted to compare novel and established practices [1,2] or compare various popular manipulations to training protocols [3,4] in attempts to establish best practice more objectively. Randomised controlled trials (RCTs) represent the most common design used in this context and are considered in many fields to be at the top of any evidence hierarchy.[5] Previous reviews of RCTs in strength and conditioning have shown that most studies employ a pre-post design (single baseline and post-intervention measurement) with interventions lasting between eight to twelve weeks.[6,7] These same reviews also highlight that studies generally comprise small sample sizes, relatively untrained participants, and multiple outcomes across a range of domains (e.g., strength, power, and sprint performance).[6,7] Whilst most interventions, especially those with relatively untrained participants result in adaptations and improved outcomes that are readily observable and easy to identify, mean differences between two interventions (average treatment effect, abbreviated as ATE) are likely to be much more difficult to identify.[7] Given the main aim of RCTs conducted in strength and condition is to distinguish between two interventions that both result in improvements, it is important to clearly assess which factors tend to limit aims being achieved and the magnitude of any subsequent problems within the evidence base.

Simulations using information obtained from previous large reviews in strength and conditioning provide a means of exploring how well RCTs are likely to meet their aims. The more realistic the data generating mechanisms included, the more insightful the generated results will be. Important factors for RCTs are likely to include expected improvements across time, correlations in improvements across outcomes, variation in improvements across participants, magnitude of the ATE, and magnitude of measurement errors. Additionally, there are multiple statistical approaches that can be used to assess ATE, including the specific statistical tests chosen [8] and construction of hypotheses to account for multiple outcomes.[9] Review of RCTs performed in strength and conditioning shows that most studies test for ATE using analysis of variance (ANOVA) and specifically the interaction between participant repeated measurements (i.e., Time) and the grouping factor.[10-18] In contrast, in many other disciplines analysis of covariance (ANCOVA) is recommended for pre-post designs beyond ANOVA or analysis of post-intervention values (e.g., with a T-test), due to lower bias and superior precision and statistical power.[19] Concern that ANCOVA is not the default choice in the general area of exercise science has previously been made.[20] It is expected that ANCOVA will provide advantages over ANOVA or Post-Score tests where there are large baseline imbalances and where baseline values are associated with change values.[19] Both scenarios are plausible in strength and conditioning where sample sizes are generally very small, increasing the probability of large baseline imbalances, and it is often postulated that negative relationships between baseline and change values occur due to diminishing returns of training.[21] This latter effect is referred to as an intervention differential effect (IDE) and can be challenging to identify due to regression to the mean effects.[21]

The inclusion of many outcomes within a single study may also have important implications for the accuracy of inferences made and the robustness of the overall evidence base created. Testing of multiple outcomes has been suggested to be a major factor in the replication crisis in science.[22] A review of RCTs in strength and conditioning identified that the median number of outcomes measured in a single study was four, with interquartile range of two to seven.[6] The most common view with multiple testing is that some form of alpha adjustment is always required to reduce the occurrence of Type I errors.[23] Alternative and more nuanced approaches, however, have been presented including consideration of the different hypothesis constructions taken.[9] This includes the perspective that alpha adjustment is not required with independent testing where declarative statements of superiority are restricted only to outcomes and their respective domains observed as significant.[9] In contrast, alpha adjustment may be required in disjunction testing where researchers declare an intervention to be superior if any outcome measured is observed as significant. [9] In strength and conditioning research, hypothesis testing is rarely explicitly stated in independent, disjunction, or conjunction modes. Based on authors discussions, a disjunction approach can often be inferred and in many of these cases multiple testing adjustment is made with Bonferroni corrections.[10-18] This approach assumes that that the different tests conducted are independent,[24] however, review of both within and between group analyses of change in multiple outcomes in strength and conditioning shows large correlations.[7,25] As a result, Bonferroni adjustments are likely to be overly conservative and further reduce what is likely to be low statistical power given small ATEs and sample sizes common in strength and conditioning. To provide an assessment of many of these statistical issues the present study was conducted. The purpose of this simulation study was to generate realistic data patterns informed by previous research across a range of scenarios consistent with intervention comparisons in strength and conditioning. Different statistical analyses were then performed on the simulated data to establish conditions that would generate correct inferences or lead to frequent Type I or Type II errors.

Methods

Approach to the problem

Simulation provides the only means of knowing the true data generating mechanism behind measurements and thereby the precise effects of manipulating many modifiable aspects of a research study on the accuracy of inferences made over the long run. In this study, results from recent large scale meta-analyses in strength and conditioning were used to generate realistic data patterns across a range of scenarios. Different statistical analyses and hypothesis constructions were applied to the data to determine rates of correct inferences and errors, and the factors that influenced these distinctions. Focus was placed on the ATE between a "reference" training intervention known to be successful and a new "testing" intervention hypothesised to be superior. Factors manipulated to influence the accuracy of inferences were: 1) pattern of improvement in the reference intervention; 2) the strength of IDE caused by baseline values; 3) the ATE magnitude; 4) the magnitude of baseline imbalance; 5) the sample size in each group; 6) the magnitude of measurement errors; 7) the statistical test performed; and 8) the number of outcomes included in disjunction hypothesis tests.

A potential limitation of simulation-based techniques is that they can provide limited understanding of why manipulating a factor or combination of factors affect the accuracy of inferences made. For that reason, a detailed presentation of the statistical mathematics relevant to the approaches and data generating mechanisms are presented in the Appendices. Derivations of these results are also provided for completeness.

Simulation

Baseline data from individual outcomes Y_{ijk} where $i = 1,2,\ldots,N$ indexes participants, $j = 0,1$ indexes the reference and testing interventions, and $k = 0,1$ indexes the baseline and post-intervention measurements, were simulated from the standard normal distribution $Z \sim N(0,1^2)$ with subsequent scaling applied to contextualise to strength and conditioning. A total of nine outcomes were simulated and conceptualised as three outcomes from three different domains (strength, power, and sprint), such that the joint baseline distribution was a multivariate normal distribution with intra-domain correlations of 0.9 and inter-domain correlations of 0.7.[25] In addition to standard baseline simulations with independent draws for both reference and testing interventions, a simple forced baseline imbalance condition was also adopted. For this condition baseline data were simulated for the reference intervention and a value of 0.5 subtracted to obtain participant data for the testing intervention. The probability of obtaining an unequal baseline $(\bar{Y}_{.10} - \bar{Y}_{.00})$ is $P(|\bar{Y}_{.10} - \bar{Y}_{.00}| > k\sigma) = P\left(|Z| > k\sqrt{n/2}\right)$.[26] To reflect the sample sizes commonly recruited in strength and conditioning and what may be considered feasible with substantial investment, group sizes of N=10,15,25, and 50 were investigated. Using the standard normal distribution, a baseline imbalance of at least 0.5 should be expected to occur on approximately 20.6, 17.2, 7.7, and 1.2% of occasions for N=10,15,25, and 50, respectively. Therefore, the simple forced imbalance approach was conceptualised primarily for $N = 10$ and 15 where such an imbalance would occur relatively frequently. In addition, only 20% of previous studies in strength and conditioning have recruited more than 15 participants per group.[6]

Post intervention data were then simulated for the reference intervention. Three different conditions were investigated including a small, medium and large improvement based on outcome domain specific data established previously.[6] Multivariate normal distributions for the change values were used with intra-domain correlations of 0.7 and inter-domain correlations of 0.5.[7] Two different data generating mechanisms were considered, the first referred to as the independent case that assumed a normal distribution with mean equal to the small, medium, or large effect size, and standard deviation equal to 1.25 times the medium effect (based on the median value obtained from an unpublished review of 73 studies reporting change score means and standard deviations). This mechanism assumed inter-individual variation in response but assumed that variation was not influenced by the baseline value. In notation we have $Y_{ij1} = Y_{ij0} + \Delta_j + \xi_{ij1}$, where Δ_j is a constant describing the mean change in group j, and $\xi_{ij1} \sim N(0, \nu_1^2)$ describes the variation in true change scores, which was equivalent for both groups. The second data generating mechanism was referred to as the constrained linear case and assumed a normal distribution with the same mean as the independent case, but the change was influenced by the baseline value. In notation we have $Y_{ij1} = Y_{ij0} + \Delta_j + \tau Y_{ij0} + \tilde{\xi}_{ij1}$, where τ sets the slope of the linear relationship between the true change score and baseline true score which is the same for each group, and $\tilde{\xi}_{ij1} \sim N(0, \tilde{\nu}_1^2)$ describes any further variation in true change score and is independent from Y_{ij0}. The data generating mechanism is constrained by the fact that τ and $\tilde{\nu}_1^2$ are the same across the groups. Two constrained linear conditions were examined where τ accounted for either 25 or 50% of the overall change variation. To ensure that overall variation in change was the same across both the independent and constrained linear case, the following relations were set: $\tau = -\sqrt{c}\nu_1$ and $\tilde{\nu}_1^2 = (1-c)\nu_1^2$, where c=0.25 or 0.5. For detailed coverage of the data generating mechanisms and their statistical properties see the Appendices.

To simulate the test intervention, an additive term was included to generate the ATE. In total four conditions were assessed including a zero, small, medium, or large ATE. The small, medium, and large ATE were obtained from comparative effectiveness distributions obtained previously and were the same for all three outcome domains.[7] The zero ATE condition was ultimately used to quantify proportion of Type I errors, and the small, medium, and large conditions used to quantify proportion of Type II errors and statistical power. Measurement errors were added to baseline and post-intervention data with small, medium, and large error values considered. Three different statistical tests were conducted on all data sets including Post-Score (representing a T-test on post-intervention values only), ANOVA and ANCOVA tests. Each testing approach was conducted within a regression framework so that the ATE estimate and its variance (reciprocal of precision) could be calculated along with their *p* values and the subsequent proportion of Type I and Type II errors. Derivation of the ATE estimates for the different tests, bias, precision, and bias conditioned on baseline imbalance are presented in the Appendices. For each simulated iteration, the tests were performed across all conditions and ATE estimate, standard error and *p*-value recorded. Disjunction hypothesis testing was considered within a domain (e.g., if any of the three outcomes within a domain was identified as 'significant' at $p<0.05$ then the ATE was declared as non-zero) and across all domains (e.g., if any of the nine outcomes returned $p<0.05$ then the ATE was declared as non-zero). All parameters for the simulations are presented in Table 1. Simulations were performed in R,[27] with the doParallel package [28] used to conduct parallel computation with 10,000 iterations performed for each scenario investigated. R code and subsequent testing for simulations are presented in the Appendices.

Table 1: Parameters for simulations separated by category.

Reference intervention effect size	Sample sizes	Average treatment effect	Change score Standard deviation	Error magnitude	Baseline imbalance
Strength Small: 0.25	Very small: 10	Zero: 0	Small: 0.75	Small: 0.1	Zero: 0
Power Small: 0.20	Small: 15	Small: 0.15	Medium: 0.625	Medium: 0.25	Negative: -0.5
Sprint Small: 0.05	Medium: 25	Medium: 0.30	Large: 0.50	Large: 0.5	Positive: 0.5
Strength Medium: 0.60	Large: 50	Large: 0.50			
Power Medium: 0.50					
Sprint Medium: 0.40					
Strength Large: 1.0					
Power Large: 0.80					
Sprint Large: 0.70					

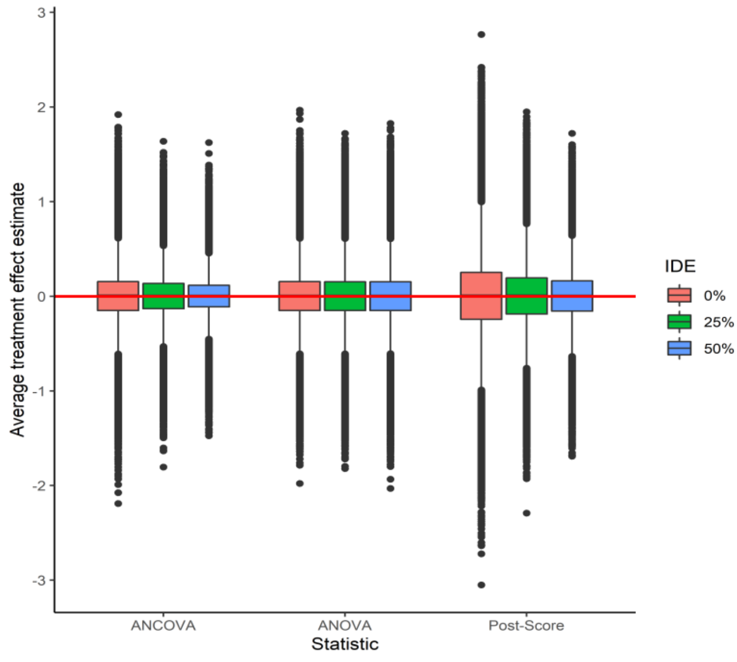
Doi: 10.51224/SRXIV.363. SportRχiv Preprint version 1

Results

Zero average treatment effects

Assessments of bias and precision of the different statistical analyses without forced baseline imbalances are illustrated in Figure 1. The results demonstrate no bias and greater precision with ANCOVA and ANOVA compared with Post-Score tests. Consistent with derived results (Appendix D), precision increased for ANCOVA and Post-Score tests with greater IDE (Figure 1). Assessment of Type I errors are presented in Table 1. For independent testing and no forced baseline imbalances, Type I errors were close to 5% regardless of IDE for all tests. A slight inflation (~5.3 to 5.7%) was observed for ANOVA testing with smaller sample sizes (Appendix H). Slightly smaller proportion of Type I errors were identified for Post Score testing compared with ANOVA and ANCOVA for disjunction testing. For three and nine outcomes the proportion of Type I errors were ~13 and 30% for ANOVA and ANCOVA, respectively; and ~10 and 23% for Post Score testing, respectively. These differences were associated with higher correlations of ATE estimates for Post-Score compared with ANOVA and ANCOVA testing. Assessment of Type I errors with forced baseline imbalances were assessed for sample sizes of 10 and 20 per group (Table 1). Greater proportion of Type I errors were obtained for sample sizes of 20 compared with 10 for both ANOVA and Post Score tests, reflecting the stronger confounding and reduced likelihood of a half standard deviation baseline imbalance for the larger sample size.

Figure 1: Distribution of average treatment estimates for common statistical tests across simulations with zero average treatment effect and different levels of intervention differential effects (IDE).



Distributions comprise simulations without forced baseline imbalance across all outcome domains, error magnitudes and sample sizes investigated.

Table 2: Proportion of Type I errors under different data generating mechanisms, statistical tests, and degree of multiple testing.

Test	Intervention differential effect	Independent testing	Disjunction testing three outcomes	Disjunction testing nine outcomes
Random baseline imbalance				
T-test	Zero	4.9	9.9	21.3
T-test	25%	5.0	10.4	23.2
T-test	50%	4.9	10.8	24.3
ANOVA	Zero	5.4	13.3	31.8
ANOVA	25%	5.3	13.0	30.5
ANOVA	50%	5.3	12.6	29.2
ANCOVA	Zero	4.9	12.3	29.5
ANCOVA	25%	4.9	12.4	29.8
ANCOVA	50%	4.9	12.5	30.5
Forced baseline imbalance (n=10)				
T-test	Zero	5.0	11.3	24.8
T-test	25%	5.5	12.5	27.3
T-test	50%	5.4	12.6	28.3
ANOVA	Zero	5.7	14.2	33.8
ANOVA	25%	6.3	15.3	34.3
ANOVA	50%	6.5	15.6	34.7
ANCOVA	Zero	5.0	12.7	30.4
ANCOVA	25%	5.0	12.7	30.7
ANCOVA	50%	5.1	12.7	30.7
Forced baseline imbalance (n=20)				
T-test	Zero	8.1	17.6	35.8
T-test	25%	8.3	18.1	37.3
T-test	50%	8.0	18.3	38.0
ANOVA	Zero	6.5	13.4	31.9
ANOVA	25%	7.2	16.6	36.4
ANOVA	50%	8.5	19.5	41.0
ANCOVA	Zero	5.1	12.7	30.3
ANCOVA	25%	5.2	12.7	30.6
ANCOVA	50%	5.0	12.7	30.6

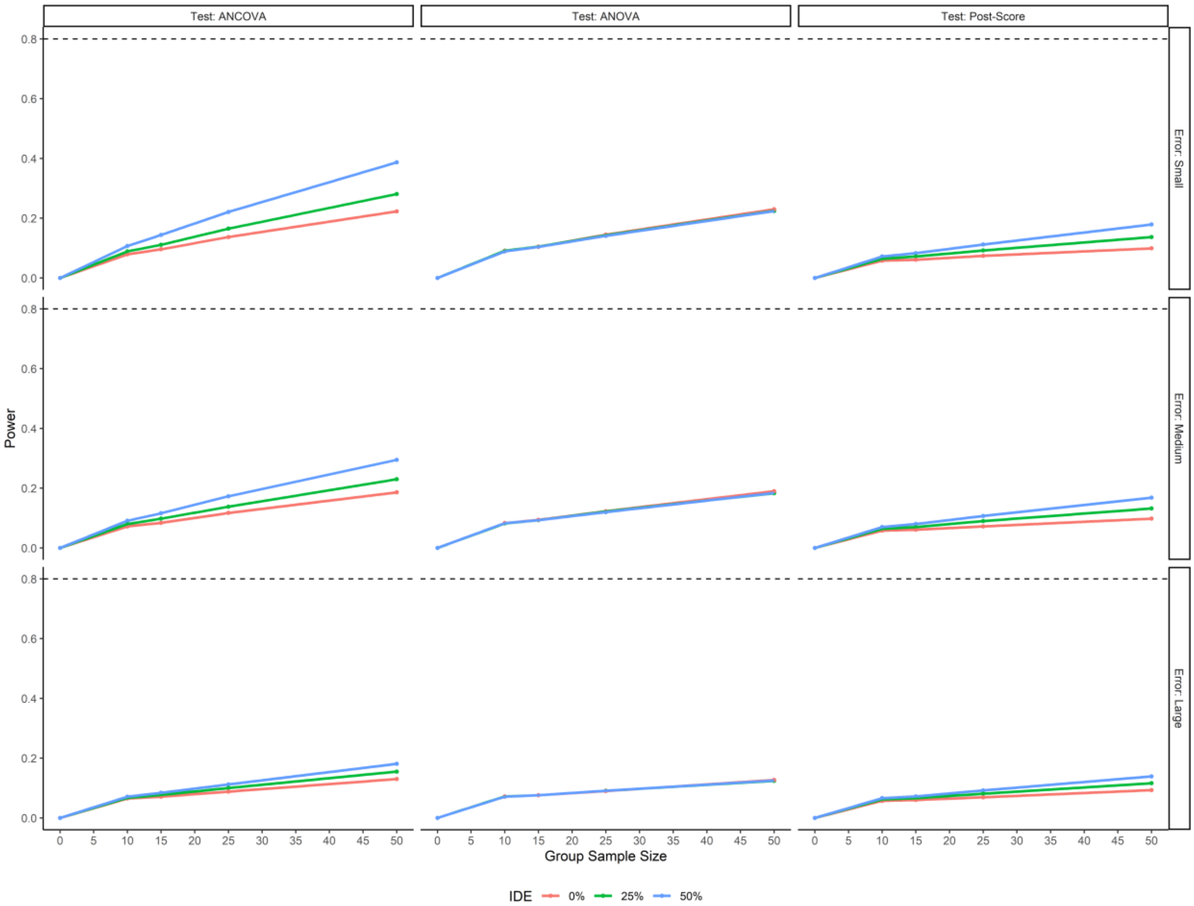
Non-zero average treatment effects

Illustration of statistical power sample size curves without forced baseline imbalance for the three statistical tests across different ATE, IDE, and error magnitudes are presented in Figures 2, 4 and 6. The results show that statistical power was greatly influenced by error magnitudes with statistical power tending to decrease by ~ 0.2 between error magnitudes identified as small and large. IDE magnitudes did not influence statistical power when conducting ANOVAs, but increased statistical power was obtained when using ANCOVA and Post-Score tests with greater IDE. Increases in statistical power of 0.2 to 0.3 were observed between zero and 50% IDE for both ANCOVA and Post-Score tests. The most substantive factor in determining statistical power was ATE. For small ATE, statistical power generally did not exceed 0.4 and even for sample sizes of 50 was less than 0.2 when combined with large measurement errors. In contrast, for large ATE, statistical power of at least 0.8 was achieved in a limited number of cases with sample sizes of 25 but was achieved in many cases for sample sizes of 50. Of note was that with large ATE and large measurement errors, ANOVA tests tended not to exceed statistical power of 0.8 with sample sizes of 50. Results also showed that statistical power was influenced by the variation in change scores within an intervention group, as demonstrated by systematic differences in statistical power between the different outcome domains (see Appendix H).

Change in statistical power with forced baseline imbalance compared to the standard randomised case is illustrated in Figures 3,5 and 7. Results show that statistical power exhibited minimal change when performing ANCOVAs. In contrast, large and contrasting changes were identified for ANOVA and Post-Score tests, with larger differences with increased ATE. ANCOVA was only influenced when performed on data with some magnitude of IDE. The results show that with a forced positive imbalance (greater baseline scores for the test intervention) the change scores were reduced for the test intervention such that statistical power reduced for ANOVA. In contrast, for forced positive imbalance the post-intervention scores tended to be higher in absolute magnitude increasing statistical power for Post-Score tests.

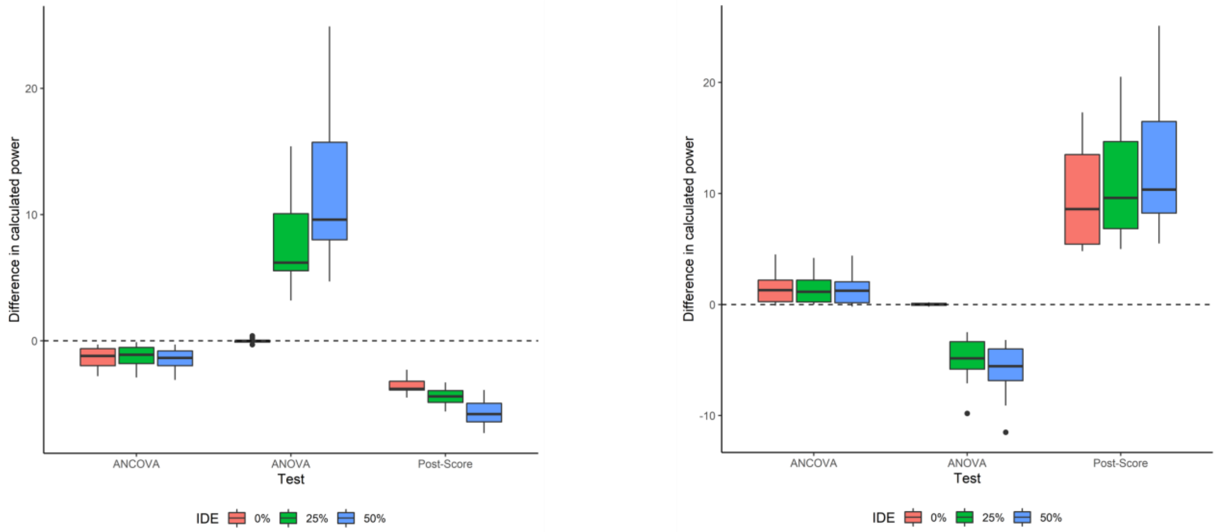
Doi: 10.51224/SRXIV.363. SportRχiv Preprint version 1

Figure 2: Statistical power sample size curves for small average treatment effects across different statistical tests, measurement error magnitudes and intervention differential effects (IDE).



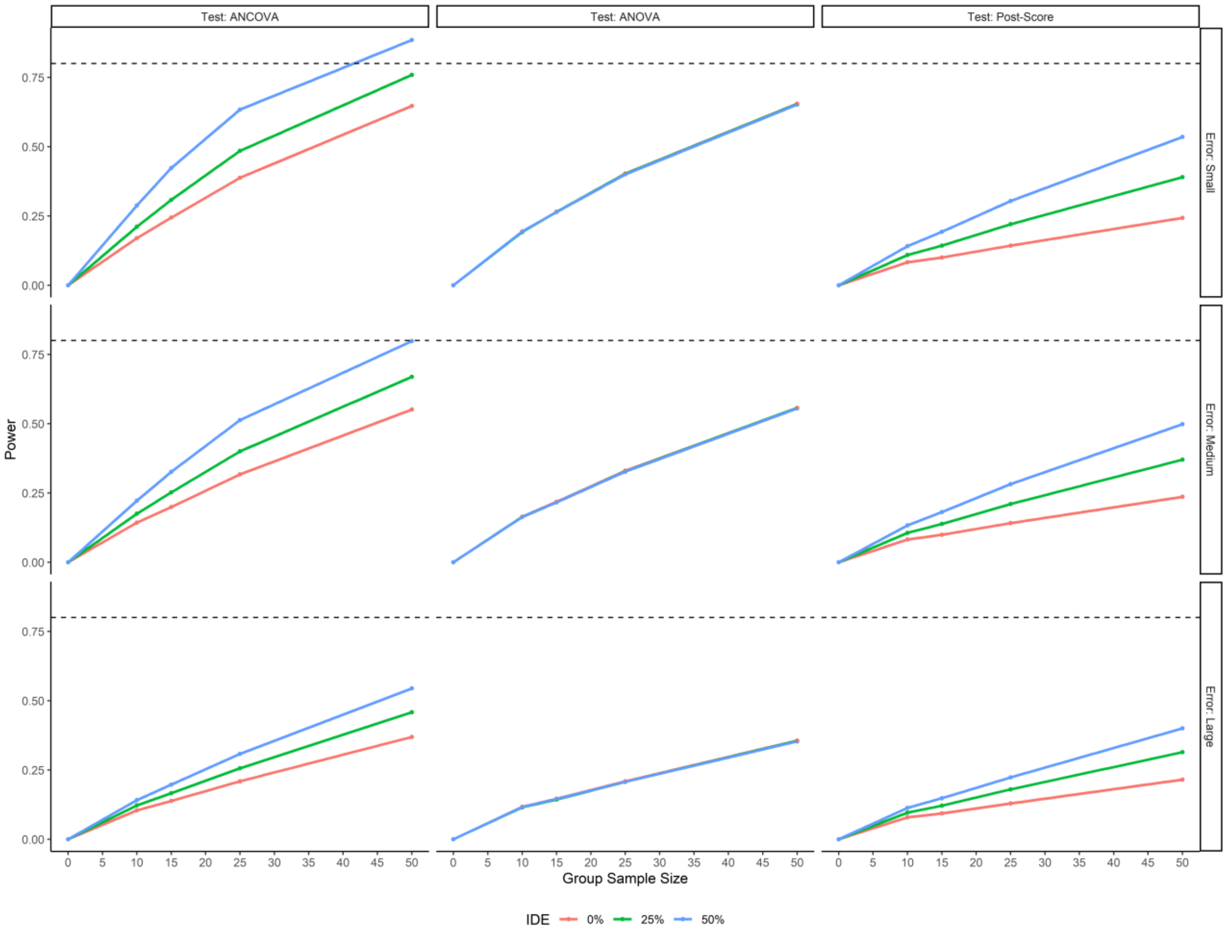
Dashed lines illustrate power of 0.8 that is often selected to justify sample size.

Figure 3: Change in proportion of tests returned as significant for small average treatment effects with forced baseline imbalances (negative imbalance testing group starts with lower values: Left; positive imbalance testing group starts with higher values) and group sample sizes of 10 or 20.



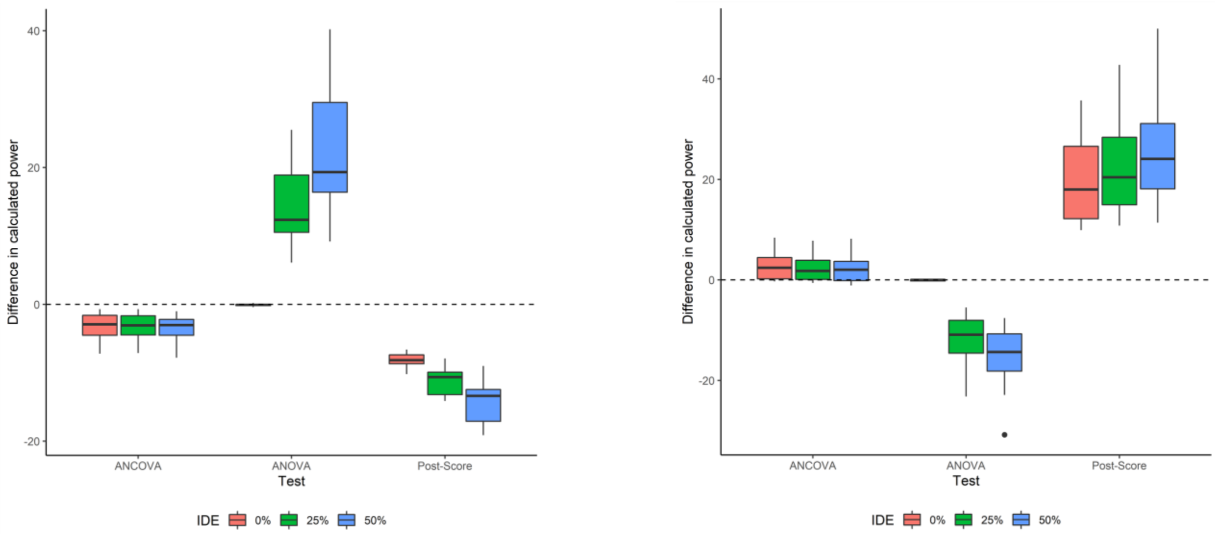
Positive values indicate that the imbalance increased the proportion of tests returned as significant, and negative values the opposite. IDE: Intervention differential effects.

Figure 4: Statistical power curves for medium average treatment effects across different statistical tests, sample sizes, measurement error magnitudes and intervention differential effects (IDE).



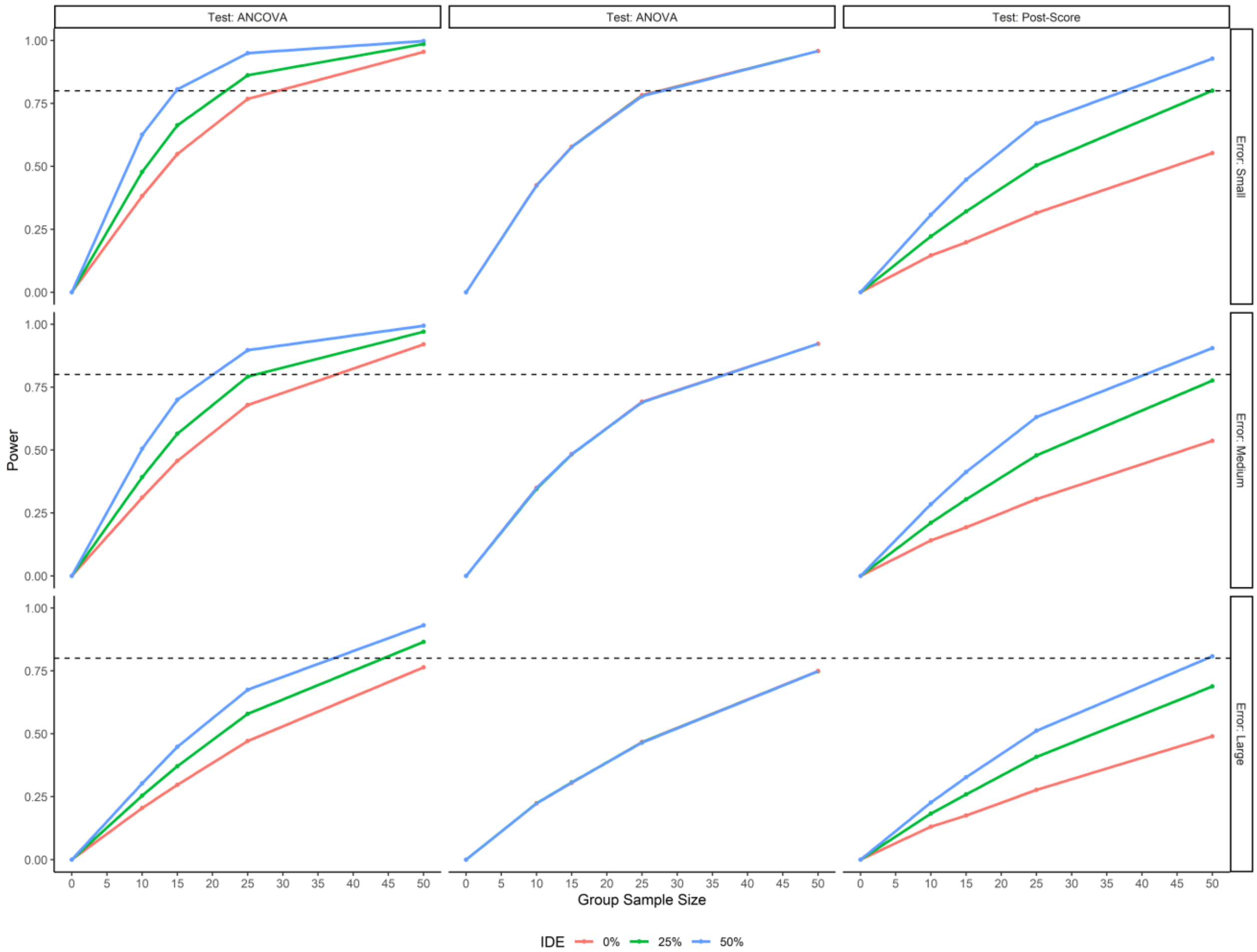
Dashed lines illustrate power of 0.8 that is often selected to justify sample size.

Figure 5: Change in proportion of tests returned as significant for medium average treatment effects with forced baseline imbalances (negative imbalance testing group starts with lower values: Left; positive imbalance testing group starts with higher values) and group sample sizes of 10 or 20.



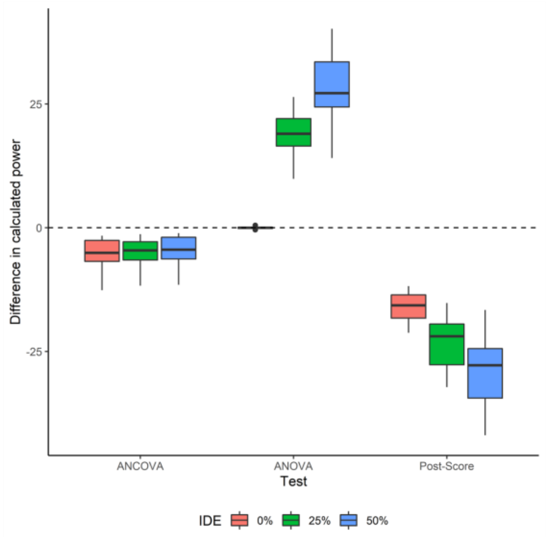
Positive values indicate that the imbalance increased the proportion of tests returned as significant, and negative values the opposite. IDE: Intervention differential effects.

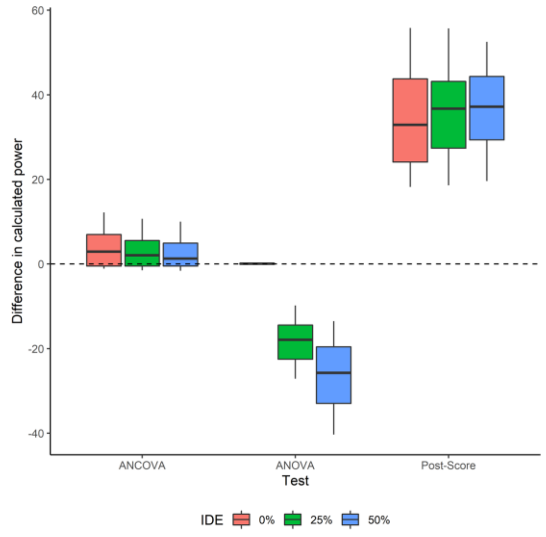
Figure 6: Statistical power curves for large average treatment effects across different statistical tests, sample sizes, measurement error magnitudes and intervention differential effects (IDE).



Dashed lines illustrate power of 0.8 that is often selected to justify sample size.

Figure 7: Change in proportion of tests returned as significant for large average treatment effects with forced baseline imbalances (negative imbalance testing group starts with lower values: Left; positive imbalance testing group starts with higher values) and group sample sizes of 10 or 20.





Positive values indicate that the imbalance increased the proportion of tests returned as significant, and negative values the opposite. IDE: Intervention differential effects.

Discussion

The results from this simulation study show that several factors including the size of the ATE, group sample sizes, the data generating mechanism, the pattern of change, the magnitude of measurement errors, the statistical test performed, and the mode of multiple testing (e.g., independent or disjunction) can have substantial influence on the accuracy of inferences made in pre-post RCTs in strength and conditioning. In general, the results of the simulation study support previous recommendations of using ANCOVAs over ANOVA or T-tests on post score measurements.[29] The results from this simulations study also, however, reinforce the extreme limitation of sample sizes commonly used in strength and conditioning, especially when ATEs are expected to be small such as the case when comparing only slight modifications of accepted training practices. The results also clearly illustrate the importance of selecting outcomes and procedures that create small measurement errors.

The results of this study agree with previous reviews of common statistical methods to analyse pre-post RCTs and the superiority of ANCOVA tests. [29] Here, the results show that where there is IDE and baseline scores are negatively related to change scores, the precision of ANCOVAs increases and exceeds ANOVA tests, that appear to be most common in strength and conditioning. The greater the IDE the greater the precision with ANCOVAs that may have a meaningful influence on statistical power. Based on the simulation parameters used here, IDE may increase statistical power of ANCOVA by ~0.2 to 0.3 beyond that achieved with ANOVA. The results from this study also show ANCOVA tests are superior to ANOVA and Post-Score testing when there is IDE and baseline imbalance. With the simple forced baseline imbalance model used here, a positive baseline imbalance would occur when by chance the test intervention had higher true scores than the reference intervention. With a negative IDE, because the test intervention included individuals with higher baseline scores, they would tend to experience lower change scores, such that if there was a positive ATE, this would be less likely to be declared when using an ANOVA, but more likely to be declared when using Post-Score testing. In contrast little change in statistical power was observed with the ANCOVA between forced baseline imbalance or not, and as shown in the appendices, this slight conditional bias occurs due to measurement error. Whilst baseline imbalances are probabilistic such that over the long run effects are cancelled out, in practice we do not conduct hundreds of RCTs on specific comparisons and so assessing statistical performance conditional on baseline imbalance is warranted.[26]

Whilst ANCOVA tests are generally preferred when analysing pre-post RCTs, it is important to note their underlying assumptions. The standard ANCOVA assumes that any IDE is consistent between the two groups. This assumption may not be appropriate for example, when comparing an active intervention with a non-exercise control. In this case, we may expect a negative relationship between baseline and post-intervention for the active group, or no relationship or a weaker relationship with the non-exercise control. It is also possible that different active interventions in strength and conditioning would lead to different IDE relationships. In each of these cases, an ANCOVA with an additional interaction term can be included to account for the different slopes.[8] Further study is required, however, to examine the sample sizes and conditions required to accurately estimate any difference in slopes and the extent to which inferences are affected.

A main take away from this simulation study is that regardless of the statistical test used, common sample sizes and testing approaches used in pre-post RCTs in strength and condition will lead to frequent errors in inferences. In the case where there is no ATE, the results show that testing of a single outcome will lead to Type I errors close to the alpha set (e.g., 0.05). However, as identified by previous large reviews in strength and conditioning, most RCTs measure multiple outcomes,[6] often these are from the same domain (e.g., assessment of maximum strength with the bench press, squat, and deadlift). The desire to collect data from multiple outcomes and multiple outcome domains is understandable given the amount of resource required to undertake an intervention study with multiple groups, even with the relatively small number of participants typically recruited. The results obtained in the present study, however, show that when performing disjunction testing with three outcomes in the same domain Type I errors are likely to occur between ~10 and 13% of occasions, which may increase to ~15 to 18% of occasions when there are baseline imbalances. Similarly, with disjunction testing with nine outcomes across multiple domains, Type I errors may occur between 20 and 40% depending on the specifics of the data and the statistical test used. To limit this clear problem, researchers may choose a smaller number of outcomes and perform independent testing such that declarative statements of superiority are limited to the outcomes that reach statistical significance, and not amalgamated into statements regarding overall superiority based on multiple testing. In contrast, disjunction testing with alpha adjustment might be considered. The results of this study show that because of the expected relationships between tests, the proportion of type I errors are not as large as would occur between independent tests, therefore adjustments such as Bonferroni, that is commonly used in strength and conditioning, are likely to be too conservative. Given the low statistical power that generally exists, however, alpha adjustment is unlikely to be a sensible solution as this will only further decrease statistical power.

Across the simulations large differences in statistical power were identified. The most relevant factors were group sample size, magnitude of the ATE, magnitude of measurement errors, and magnitude of IDE. In the worst-case scenario with group sizes of 10, small ATE, large measurement errors and zero IDE, statistical power for independent testing was likely to be ~0.1. It is important to note, that this configuration represents a sizeable proportion of previous research and if studies were limited to a single statistical test, concern should exist for accuracy of studies reporting no statistical difference. With small ATE, no scenario investigated could obtain statistical power greater than ~0.4. Given most RCTs aim for statistical power of at least 0.8, these results show how limited standard pre-post designs are for strength and conditioning research when dealing with small ATE. Even with medium ATE, most scenarios with sample sizes of 50 did not lead to statistical power of at least 0.8, with this threshold generally reserved for large ATE and sample sizes of close to 50. The finding that statistical power was influenced to such a large extent by measurement error, IDE and even by the pattern of variance, highlights the potential limitation of standard power calculations used to obtain sample sizes with software such as G*Power 3.1 that include minimal parameters in calculations.[30] This limitation and the potential for measurement error to drastically reduce statistical power and increase sample size requirements by more than a factor of five has been highlighted previously.[31] Instead, more complex calculations [31] or simulation-based approaches that simulate data based on results from pilot studies, or as was done here based on results from meta-analyses, may lead to more accurate power calculations and sample size targets.

The findings from this study highlight a critical limitation of most pre-post RCT studies in strength and conditioning and the likely existence of many errors in inference in the literature. Whilst it may be tempting to suggest that research should simply focus on single outcomes and greatly increase sample sizes beyond 50 and potentially beyond 100, the fact that these studies have only rarely been conducted indicates that this is not likely to be a realistic change. Instead, more innovative modifications to RCTs may be required. One such modification may include the use of plausible sample sizes between 20 and 50 but combined with high-frequency outcome measurement. In some scenarios in strength and conditioning this may be relatively easy to achieve. For example, research comparing training interventions and their effects on hypertrophy could measure muscle thickness using ultrasound prior to each training session. For testing that is likely to interfere with the training intervention (e.g. 1RM testing and strength interventions), frequent direct measurement may not be possible. However, a range of methods now exist to predict outcomes from performances within the actual training session. Examples include the use of velocity-based methods to predict maximum strength during maximum intention sets,[32] or repetition maximums assessed with repetitions in reserve.[33] Whilst these methods are likely to introduce increased measurement error that was shown in this study to be detrimental to statistical power, frequent measurement may offset and ultimately provide appropriate statistical power. Further research is required to determine the best selection of statistical methods, outcome measurements, measurement frequency and sample size to surpass the current severe limitations with pre-post RCT designs that are used currently in strength and conditioning.

References

1. Orange ST, Hritz A, Pearson L, Jeffries O, Jones TW, Steele J. Comparison of the effects of velocity-based vs. traditional resistance training methods on adaptations in strength, power, and sprint speed: A systematic review, meta-analysis, and quality of evidence appraisal. Journal of Sports Sciences. 2022;40(11):1220-34. https://doi.org/10.1080/02640414.2022.2059320
2. Lopes JS, Machado AF, Micheletti JK, De Almeida AC, Cavina AP, Pastre CM. Effects of training with elastic resistance versus conventional resistance on muscular strength: A systematic review and meta-analysis. SAGE open medicine. 2019: https://doi.org/10.1177/2050312119831116
3. Caldas LC, Guimarães-Ferreira L, Duncan MJ, Leopoldo AS, Leopoldo AP, Lunz W. Traditional vs. undulating periodization in the context of muscular strength and hypertrophy: a meta-analysis. Int J Sports Sci. 2016;6(6):219-9. https://doi.org/10.5923/j.sports.20160606.04
4. Buskard AN, Gregg HR, Ahn S. Supramaximal eccentrics versus traditional loading in improving lower-body 1RM: A meta-analysis. Research quarterly for exercise and sport. 2018 Jul 3;89(3):340-6. https://doi.org/10.1080/02701367.2018.1472365
5. Clarke B, Gillies D, Illari P, Russo F, Williamson J. Mechanisms and the evidence hierarchy. Topoi. 2014;33:339-60. https://doi.org/10.1007/s11245-013-9220-9
6. Swinton PA, Burgess K, Hall A, Greig L, Psyllas J, Aspe R, Maughan P, Murphy A. Interpreting magnitude of change in strength and conditioning: Effect size selection, threshold values and Bayesian updating. Journal of sports sciences. 2022;40(18):2047-54. https://doi.org/10.1080/02640414.2022.2128548
7. Swinton, PA. Murphy,A.Comparative effect size distributions in strength and conditioning and implications for future research: A meta-analysis. 2022. Pre-print available from SportRχiv. https://doi.org/10.51224/SRXIV.202
8. Wan F. Statistical analysis of two arm randomized pre-post designs with one post-treatment measurement. BMC medical research methodology. 2021 Dec;21(1):1-6. https://doi.org/10.1186/s12874-021-01323-9
9. Rubin M. When to adjust alpha during multiple testing: A consideration of disjunction, conjunction, and individual testing. Synthese. 2021 Dec;199(3-4):10969-1000. https://doi.org/10.1007/s11229-021-03276-4

10. Lum D, Barbosa TM, Aziz AR, Balasekaran G. Effects of isometric strength and plyometric training on running performance: a randomized controlled study. Research Quarterly for Exercise and Sport. 2023 Jan 2;94(1):263-71. https://doi.org/10.1080/02701367.2021.1969330
11. Sinkovic F, Novak D, Foretic N, Kim J, Subramanian SV. The plyometric treatment effects on change of direction speed and reactive agility in young tennis players: a randomized controlled trial. Frontiers in Physiology. 2023;14. https://doi.org/10.3389/fphys.2023.1226831
12. McQuilliam SJ, Clark DR, Erskine RM, Brownlee TE. Effect of High-Intensity vs. Moderate-Intensity Resistance Training on Strength, Power, and Muscle Soreness in Male Academy Soccer Players. Journal of Strength and Conditioning Research. 2023 Jun 19;37(6):1250-8. https://doi.org/10.1519/JSC.0000000000004387
13. Seo MW, Lee JM, Jung HC, Kim JY, Song JK. Identification of the Optimal HIIT Protocol for Fatigue Resistance in Adolescent Athletes: A Randomized Controlled Trial. Kinesiology. 2022 Dec 31;54(2):256-67.
14. Roso-Moliner A, Mainer-Pardos E, Arjol-Serrano JL, Cartón-Llorente A, Nobari H, Lozano D. Evaluation of 10-week neuromuscular training program on body composition of elite female soccer players. Biology. 2022;11(7):1062. https://doi.org/10.3390/biology11071062
15. Singh G, Kushwah GS, Singh T, Thapa RK, Granacher U, Ramirez-Campillo R. Effects of sand-based plyometric-jump training in combination with endurance running on outdoor or treadmill surface on physical fitness in young adult males. Journal of Sports Science & Medicine. 2022;21(2):277. https://doi.org/10.52082/jssm.2022.277
16. Brini S, Boullosa D, Calleja-González J, Ramirez-Campillo R, Nobari H, Castagna C, Clemente FM, Ardigò LP. Neuromuscular and balance adaptations following basketball-specific training programs based on combined drop jump and multidirectional repeated sprint versus multidirectional plyometric training. Plos one. 2023;18(3):e0283026. https://doi.org/10.1371/journal.pone.0283026
17. Jiang D, Xu G. Effects of chains squat training with different chain load ratio on the explosive strength of young basketball players' lower limbs. Frontiers in Physiology. 2022;13:979367. https://doi.org/10.3389/fphys.2022.979367
18. Asencio P, Hernández-Davó JL, García-Valverde A, Sabido R. Effects of flywheel resistance training using horizontal vs vertical exercises. International Journal of Sports Science & Coaching. 2022 Nov https://doi.org/10.1177/17479541221135372

19. Egbewale BE, Lewis M, Sim J. Bias, precision and statistical power of analysis of covariance in the analysis of randomized trials with baseline imbalance: a simulation study. BMC medical research methodology. 2014;14(1):1-2. c10.1186/1471-2288-14-49
20. Atkinson G, Williamson P, Batterham AM. Issues in the determination of 'responders' and 'non-responders' in physiological research. Experimental Physiology. 2019;104(8):1215-25. 10.1113/EP087712 10.1113/EP087712
21. Swinton, PA. The influence of baseline capability on intervention effects in strength and conditioning: A review of concepts and methods with meta-analysis. 2023. Pre-print available from SportRχiv. https://doi.org/10.51224/SRXIV.285.
22. Forstmeier W, Wagenmakers EJ, Parker TH. Detecting and avoiding likely false-positive findings–a practical guide. Biological Reviews. 2017;92(4):1941-68. https://doi.org/10.1111/brv.12315
23. Bennett CM, Wolford GL, Miller MB. The principled control of false positives in neuroimaging. Social cognitive and affective neuroscience. 2009;4(4):417-22. https://doi.org/10.1093/scan/nsp053
24. Sinclair J, Taylor PJ, Hobbs SJ. Alpha level adjustments for multiple dependent variable analyses and their applicability–a review. International Journal of Sports Science and Engineering. 2013;7(1):17-20.
25. Swinton, PA. Burges, K. Hall, A. Greig L. Psyllas J. Aspe R. Maughan P. Murphy A. A Bayesian approach to interpret intervention effectiveness in strength and conditioning: Part 2. Effect size selection and application of Bayesian updating. 2021. Pre-print available from SportRχiv.https://doi.org/10.51224/SRXIV.11
26. Wei L, Zhang J. Analysis of data with imbalance in the baseline outcome variable for randomized clinical trials. Drug information journal. 2001;35(4):1201-14. https://doi.org/10.1177/009286150103500417
27. R Core Team (2023). _R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing, Vienna, Austria.
28. Weston S, Analytics R. doParallel: Foreach parallel adaptor for the parallel package. R package version. 2019;1:15.
29. O'Connell NS, Dai L, Jiang Y, Speiser JL, Ward R, Wei W, Carroll R, Gebregziabher M. Methods for analysis of pre-post data in clinical research: a comparison of five common methods. Journal of biometrics & biostatistics. 2017;8(1):1. https://doi.org/10.4172/2155-6180.1000334
30. Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods. 2009;41, 1149-1160. https://doi.org/10.3758/BRM.41.4.1149
31. Phillips GW, Jiang T. Measurement error and equating error in power analysis. Practical Assessment, Research, and Evaluation. 2019;21(1):9. https://doi.org/10.7275/0snn-zm67

32. Greig L, Aspe RR, Hall A, Comfort P, Cooper K, Swinton PA. The predictive validity of individualised load-velocity relationships for predicting 1RM: a systematic review and individual participant data meta-analysis. Sports medicine. 2023;53(9):1693-1708. https://doi.org/10.1007/s40279-023-01854-9

33. Mansfield SK, Peiffer JJ, Hughes LJ, Scott BR. Estimating repetitions in reserve for resistance exercise: an analysis of factors which impact on prediction accuracy. The Journal of Strength & Conditioning Research. 2022. https://doi.org/10.1519/JSC.0000000000003779

Doi: 10.51224/SRXIV.363. SportRχiv Preprint version 1

Is it time to rethink pre-post randomised controlled trials in strength and conditioning? A review of statistical approaches with derivations and simulations.

Paul, A. Swinton

Appendices

The following appendices derive the results presented in the main paper, provide R code to illustrate and provide checks on the derivations, and provide R code for the simulations.

Doi: 10.51224/SRXIV.363. SportRχiv Preprint version 1

Appendix A: Basic statistical properties

In this section basic statistical properties that will be used to derive subsequent results are presented.

Property 1 (P1): Jointly normal random variables: Two random variables X, Y are said to be jointly normal if they can be expressed in the form $X = aU + bV$; $Y = cU + dV$ where U and V are independent normal random variables.

Property 2 (P2): Population mean $E(X) = \mu$ and the linearity of expectation: $E(aX + bY) = aE(X) + bE(Y)$, where a and b are constants.

Property 3 (P3): Expectation of an independent product: if X and Y are independent then $E(XY) = E(X)E(Y)$.

Property 4 (P4): Population variance and expectation: $V(X) = E(X^2) - \mu^2$.

Property 5 (P5): Variance of a linear combination: $V(aX + by) = a^2V(X) + 2abCov(X, Y) + b^2V(Y)$.

Property 6 (P6): Covariance and expectation: $Cov(X, Y) = E(XY) - \mu_X\mu_Y$.

Property 7 (P7): Covariance and correlation: $Corr(X, Y) = \rho_{XY} = \frac{Cov(X,Y)}{\sqrt{V(X)V(Y)}}$.

Property 8 (P8): Bivariate normal distribution:
$$\begin{matrix} X \\ Y \end{matrix} \sim \mathbb{N}\left(\begin{bmatrix} \mu_X \\ \mu_Y \end{bmatrix}, \begin{bmatrix} V(X) & \rho_{XY}\sqrt{V(X)V(Y)} \\ \rho_{XY}\sqrt{V(X)V(Y)} & V(X) \end{bmatrix}\right).$$

Property 9 (P9): Conditional expectation in the bivariate general normal distribution:
$$E(Y|X = x) = \mu_Y + \rho\left(\frac{\sigma_Y}{\sigma_X}\right)(x - \mu_X).$$

Property 10 (P10): Ordinary Least Square estimator: For the general linear model $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\zeta}$, where $\boldsymbol{\zeta}$ is multivariate normal with zero mean, uncorrelated and common variance σ^2. The estimator of $\boldsymbol{\beta}$ is: $\widehat{\boldsymbol{\beta}} = (\boldsymbol{X^TX})^{-1}\boldsymbol{X^Ty}$.

Property 11 (P11): Covariance of Ordinary Least Square parameter estimates: $\mathrm{Var}(\widehat{\boldsymbol{\beta}}) = \sigma^2(\boldsymbol{X^TX})^{-1}$.

Property 12 (P12): Conditional variance of bivariate normal distribution: $\mathrm{Var}(Y|X) = \mathrm{Var}(Y)(1 - \rho^2)$, where ρ is the correlation between X and Y.

Property 13 (P13): Generalized Least Square estimator: For the general linear model $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\zeta}$, where $\mathrm{Cov}(\boldsymbol{\zeta}|\boldsymbol{X}) = \boldsymbol{\Omega}$ the estimator of $\boldsymbol{\beta}$ is: $\widehat{\boldsymbol{\beta}} = (\boldsymbol{X^T\Omega^{-1}X})^{-1}\boldsymbol{X^T\Omega^{-1}y}$.

Property 14 (P14): Covariance of Generalized Least Square parameter estimates: $\mathrm{Var}(\widehat{\boldsymbol{\beta}}) = \sigma^2(\boldsymbol{X^T\Omega^{-1}X})^{-1}$.

Property 15 (P15): $\mathrm{Cov}\left(\sum_{i=1}^{m} a_iX_i, \sum_{j=1}^{n} b_jY_j\right) = \sum_{i=1}^{m}\sum_{j=1}^{n} a_i\, b_j\mathrm{Cov}\left(X_i, Y_j\right)$.

Property 16 (P16): $\mathrm{Var}(\sum_{i=1}^{n} a_iX_i) = \sum_{i=1}^{n}\frac{1}{a^2}\mathrm{Var}(X_i) + 2\sum_{i<j}\mathrm{Cov}\left(\mathrm{X}_iX_j\right)$.

Doi: 10.51224/SRXIV.363. SportRχiv Preprint version 1

Appendix B: Data generating mechanisms

In this section we introduce the notation used and explain the data generating mechanisms assumed to produce the baseline and post-intervention values for participants randomly allocated to one of two groups.

Notation

Y_{ijk} is the true score of participant i $(i = 1,2,\dots,n)$, in group j $(j = 0,1)$ at time k $(k = 0,1)$.
y_{ijk} is the observed score (true score plus measurement error). Groups $j = 0,1$ are both considered intervention groups, and times $k = 0,1$ refer to baseline and post-intervention, respectively.
Baseline we draw from a normal distribution with mean μ_0 and standard deviation σ_0 to obtain $Y_{ij0} \sim N(\mu_0, \sigma_0^2)$. We assume that j is randomly assigned with equal probability and is independent of $Y_{i.0}$.
What we observe in data collection is the true value plus error given by $y_{ijk} = Y_{ijk} + \epsilon_{ijk}$, where $\epsilon_{ijk} \sim N(0, \delta_k^2)$ is independent of Y_{ijk}.

Data generation

The baseline and post-intervention true scores are generated from a multivariate normal distribution $\begin{matrix} Y_{ij0} \\ Y_{ij1} \end{matrix} \sim \mathbb{N}\left(\begin{bmatrix} \mu_0 \\ \mu_{j1} \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \rho_j\sigma_0\sigma_{j1} \\ \rho_j\sigma_0\sigma_{j1} & \sigma_{j1}^2 \end{bmatrix}\right)$, where μ_{j1} and σ_{j1} are the group mean and standard deviation in post-intervention true scores, and ρ_j is the group correlation between baseline and post-intervention true scores. Throughout we only consider the homogenous case, that is where $\rho_0 = \rho_1$ and $\sigma_{01}^2 = \sigma_{11}^2$. We consider two homogenous cases including: 1) the independent case where $\mathrm{Corr}(Y_{ij0}, Y_{ij1} - Y_{ij0}) = 0$; and 2) the constrained linear case where $\mathrm{Corr}(Y_{ij0}, Y_{ij1} - Y_{ij0}) \neq 0$.

Independent case

For the independent case we express the data generating mechanism as
$Y_{ij1} = Y_{ij0} + \Delta_j + \xi_{ij1}$,
where Δ_j is a constant describing the mean change in group j, and $\xi_{ij1} \sim N(0, \nu_1^2)$ describes the variation in true change score which is the same across groups to fit with the homogenous case. From this data generating mechanism we have the following relationships:

$$\begin{aligned}\mathrm{Corr}(Y_{ij0}, Y_{ij1}) &= \frac{E(Y_{ij0}Y_{ij1}) - \mu_0\mu_{j1}}{\sqrt{\mathrm{Var}(Y_{ij0})}\sqrt{\mathrm{Var}(Y_{ij1})}} \\ &= \frac{E\left(Y_{ij0}(Y_{ij0} + \Delta_j + \xi_{ij1})\right) - \mu_0(\mu_0 + \Delta_j)}{\sigma_0\sqrt{\sigma_0^2 + \nu_1^2}} \\ &= \frac{\sigma_0^2 + \mu_0^2 + \mu_0\Delta_j - \mu_0(\mu_0 + \Delta_j)}{\sigma_0^2\sqrt{1 + \nu_1^2/\sigma_0^2}} \\ &= \frac{1}{\sqrt{1 + \nu_1^2/\sigma_0^2}}. \end{aligned} \qquad \text{Result 1}$$

$$\begin{aligned}\mathrm{Corr}(y_{ij0}, y_{ij1}) &= \frac{E(y_{ij0}y_{ij1}) - \mu_0\mu_{j1}}{\sqrt{\mathrm{Var}(y_{ij0})}\sqrt{\mathrm{Var}(y_{ij1})}} \\ &= \frac{E\left((Y_{ij0} + \epsilon_{ij0})(Y_{ij0} + \Delta_j + \xi_{ij1} + \epsilon_{ij1})\right) - \mu_0(\mu_0 + \Delta_j)}{\sqrt{\sigma_0^2 + \delta_0^2}\sqrt{\sigma_0^2 + \nu_1^2 + \delta_1^2}} \\ &= \frac{\sigma_0^2 + \mu_0^2 + \mu_0\Delta_j - \mu_0(\mu_0 + \Delta_j)}{\sigma_0^2\sqrt{1 + \delta_0^2/\sigma_0^2}\sqrt{1 + \nu_1^2/\sigma_0^2 + \delta_1^2/\sigma_0^2}} \\ &= \frac{1}{\sqrt{1 + \delta_0^2/\sigma_0^2}\sqrt{1 + \nu_1^2/\sigma_0^2 + \delta_1^2/\sigma_0^2}}. \end{aligned} \qquad \text{Result 2}$$

$$\begin{aligned}\mathrm{Corr}(Y_{ij0}, Y_{ij1} - Y_{ij0}) &= \frac{\mathrm{Cov}(Y_{ij0}, Y_{ij1} - Y_{ij0})}{\sqrt{\mathrm{Var}(Y_{ij0})}\sqrt{\mathrm{Var}(Y_{ij1} - Y_{ij0})}} \\ &= \frac{E\left(Y_{ij0}(Y_{ij1} - Y_{ij0})\right) - \mu_0(\mu_{j1} - \mu_0)}{\sigma_0\sqrt{2\sigma_0^2 + \nu_1^2 - 2\mathrm{Cov}(Y_{ij0}, Y_{ij1})}} \\ &= \frac{\sigma_0^2 + \mu_0\mu_{j1} - (\sigma_0^2 + \mu_0^2) - \mu_0(\mu_{j1} - \mu_0)}{\sigma_0\nu_1} \\ &= 0. \end{aligned} \qquad \text{Result 3}$$

The distribution of baseline and post-intervention true scores for the independent case are thus

$$\begin{matrix} Y_{ij0} \\ Y_{ij1} \end{matrix} \sim \mathbb{N}\left(\begin{bmatrix} \mu_0 \\ \mu_0 + \Delta_j \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_0^2 \\ \sigma_0^2 & \sigma_0^2 + \nu_1^2 \end{bmatrix}\right). \qquad \text{Result 4}$$

The distribution of baseline and post-intervention observed scores for the independent case are thus

$$\begin{matrix} y_{ij0} \\ y_{ij1} \end{matrix} \sim \mathbb{N}\left(\begin{bmatrix} \mu_0 \\ \mu_0 + \Delta_j \end{bmatrix}, \begin{bmatrix} \sigma_0^2 + \delta_0^2 & \sigma_0^2 \\ \sigma_0^2 & \sigma_0^2 + \nu_1^2 + \delta_1^2 \end{bmatrix}\right). \qquad \text{Result 5}$$

Constrained linear case

For the constrained linear case we assume the data generating model

$$Y_{ij1} = Y_{ij0} + \tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1},$$

where τ sets the slope of the linear relationship between the true change score and baseline true score which is the same for each group, and $\tilde{\Delta}_j$ sets any group offset. $\tilde{\xi}_{ij1} \sim N(0, \tilde{\nu}_1^2)$ describes any further variation in true change score not caused by differences in baseline true score and is independent from Y_{ij0}. The data generating mechanism is constrained by the fact that τ and $\tilde{\nu}_1^2$ are the same across the groups. From this data generating mechanism we have the following relationships:

$$\begin{aligned} \mathrm{Corr}(Y_{ij0}, Y_{ij1}) &= \frac{E(Y_{ij0}Y_{ij1}) - \mu_0\mu_{j1}}{\sqrt{\mathrm{Var}(Y_{ij0})}\sqrt{\mathrm{Var}(Y_{ij1})}} \\ &= \frac{E\left(Y_{ij0}\left(Y_{ij0} + \tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1}\right)\right) - \mu_0\left(\mu_0 + \tilde{\Delta}_j + \tau\mu_0\right)}{\sigma_0\sqrt{(1+\tau)^2\sigma_0^2 + \tilde{\nu}_1^2}} \\ &= \frac{\sigma_0^2 + \mu_0^2 + \mu_0\tilde{\Delta}_j + \tau(\sigma_0^2 + \mu_0^2) - \mu_0^2 - \tilde{\Delta}_j\mu_0 - \tau\mu_0^2}{\sigma_0^2\sqrt{(1+\tau)^2 + \tilde{\nu}_1^2/\sigma_0^2}} \\ &= \frac{(1+\tau)}{\sqrt{(1+\tau)^2 + \tilde{\nu}_1^2/\sigma_0^2}}. \qquad \text{Result 6} \end{aligned}$$

$$\begin{aligned} \mathrm{Corr}(y_{ij0}, y_{ij1}) &= \frac{E(y_{ij0}y_{ij1}) - \mu_0\mu_{j1}}{\sqrt{\mathrm{Var}(y_{ij0})}\sqrt{\mathrm{Var}(y_{ij1})}} \\ &= \frac{E\left(\left(Y_{ij0} + \epsilon_{ij0}\right)\left(Y_{ij0} + \tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1} + \epsilon_{ij1}\right)\right) - \mu_0\left(\mu_0 + \tilde{\Delta}_j + \tau\mu_0\right)}{\sqrt{\sigma_0^2 + \delta_0^2}\sqrt{(1+\tau)^2\sigma_0^2 + \tilde{\nu}_1^2 + \delta_1^2}} \\ &= \frac{\sigma_0^2 + \mu_0^2 + \mu_0\tilde{\Delta}_j + \tau(\sigma_0^2 + \mu_0^2) - \mu_0^2 - \tilde{\Delta}_j\mu_0 - \tau\mu_0^2}{\sigma_0^2\sqrt{1 + \delta_0^2/\sigma_0^2}\sqrt{(1+\tau)^2 + \tilde{\nu}_1^2/\sigma_0^2 + \delta_1^2/\sigma_0^2}} \\ &= \frac{(1+\tau)}{\sqrt{1 + \delta_0^2/\sigma_0^2}\sqrt{(1+\tau)^2 + \tilde{\nu}_1^2/\sigma_0^2 + \delta_1^2/\sigma_0^2}}. \qquad \text{Result 7} \end{aligned}$$

$$\begin{aligned} \mathrm{Corr}(Y_{ij0}, Y_{ij1} - Y_{ij0}) &= \frac{\mathrm{Cov}(Y_{ij0}, Y_{ij1} - Y_{ij0})}{\sqrt{\mathrm{Var}(Y_{ij0})}\sqrt{\mathrm{Var}(Y_{ij1} - Y_{ij0})}} \\ &= \frac{E\left(Y_{ij0}\left(Y_{ij0} + \tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1} - Y_{ij0}\right)\right) - \mu_0\left(\mu_0 + \tilde{\Delta}_j + \tau\mu_0 - \mu_0\right)}{\sigma_0\sqrt{\mathrm{Var}\left(Y_{ij0} + \tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1} - Y_{ij0}\right)}} \\ &= \frac{E\left(Y_{ij0}\left(\tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1}\right)\right) - \mu_0\left(\tilde{\Delta}_j + \tau\mu_0\right)}{\sigma_0\sqrt{\mathrm{Var}\left(\tilde{\Delta}_j + \tau Y_{ij0} + \tilde{\xi}_{ij1}\right)}} \\ &= \frac{\tilde{\Delta}_j\mu_0 + \tau(\sigma_0^2 + \mu_0^2) - \tilde{\Delta}_j\mu_0 - \tau\mu_0^2}{\sigma_0\sqrt{\tau^2\sigma_0^2 + \tilde{\nu}_1^2}} \\ &= \frac{\tau}{\sqrt{\tau^2 + \tilde{\nu}_1^2/\sigma_0^2}}. \qquad \text{Result 8} \end{aligned}$$

The distribution of baseline and post-intervention true scores for the constrained linear case are thus

$$\begin{matrix} Y_{ij0} \\ Y_{ij1} \end{matrix} \sim \mathbb{N}\left(\begin{bmatrix} \mu_0 \\ \mu_0(1+\tau) + \tilde{\Delta}_j \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_0^2(1+\tau) \\ \sigma_0^2(1+\tau) & (1+\tau)^2\sigma_0^2 + \tilde{\nu}_1^2 \end{bmatrix}\right). \qquad \text{Result 9}$$

The distribution of baseline and post-intervention observed scores for the constrained linear case are thus

$$\begin{matrix} y_{ij0} \\ y_{ij1} \end{matrix} \sim \mathbb{N}\left(\begin{bmatrix} \mu_0 \\ \mu_0(1+\tau) + \tilde{\Delta}_j \end{bmatrix}, \begin{bmatrix} \sigma_0^2 + \delta_0^2 & \sigma_0^2(1+\tau) \\ \sigma_0^2(1+\tau) & (1+\tau)^2\sigma_0^2 + \tilde{\nu}_1^2 + \delta_1^2 \end{bmatrix}\right). \qquad \text{Result 10}$$

Appendix C: Treatment effect estimators

Given both data generating models specified, the average treatment effect (ATE), or comparative effectiveness is defined as the difference in the expected change in true scores across the intervention between the groups $(\Delta_1 - \Delta_0)$. In practice, assessment of a treatment effect is made by selecting a treatment effect metric and an associated statistical method. Typically, this is achieved by fitting a regression model and using the least square estimator as the best estimate of the treatment effect. Associated standard errors are then used to calculate *p*-values and test the hypothesis that the treatment effect is zero. The most common regression models include: 1) post score model; 2) analysis of variance (ANOVA) interaction; and 3) analysis of covariance (ANCOVA). In the following sections we outline the regression models and calculate the least square estimator used to assess the treatment effect. Calculations are made by specifying the design matrix $\boldsymbol{X}$ for each regression model and using either the least square estimator (P10) combined with determinants and matrix algebra or direct minimisation of the sum of squares.

Post score model

The post score model includes the following regression model:

$y_{ij1} = \beta_0 + \beta_1 G_{ij} + \zeta_{ij1}$

where β_0 is used to model the expected post-intervention scores of group 0, and β_1 the ATE. In the regression model G is a binary group indicator ($0 =$ group 0, $1 =$ group 1). We note that ζ_{ij1} is used to distinguish residuals from measurement error (ϵ_{ijk}) as specified in our data generating models.

For the post score model the design matrix $\boldsymbol{X}$ comprises two columns, the first is $\mathbf{1}'$, and the second includes n_0 0's and n_1 1s, where n_0 and n_1 are the number of participants in intervention group 0 and 1, respectively. If we let $n = n_0 + n_1$, we then have $\boldsymbol{X^T X} = \begin{bmatrix} n & n_1 \\ n_1 & n_1 \end{bmatrix}$ and with $|\boldsymbol{X^T X}| = nn_1 - n_1^2 = n_1(n - n_1) = n_1 n_0$, this gives

$(\boldsymbol{X^T X})^{-1} = \begin{bmatrix} \frac{1}{n_0} & -\frac{1}{n_0} \\ -\frac{1}{n_0} & \frac{n}{n_1 n_0} \end{bmatrix}$. If we let $\bar{y}_{.01}$, $\bar{y}_{.11}$, and $\bar{y}_{.j1}$ equal the mean post-intervention observed scores from group 0, group 1, and across both groups, then we have that $\boldsymbol{X^T y} = \begin{bmatrix} \sum_{i=1}^{n} y_{ij1} = n\bar{y}_{.j1} \\ \sum_{i=1}^{n_1} y_{i11} = n_1\bar{y}_{.11} \end{bmatrix}$. The least squares estimator by P10 is thus

$$\hat{\boldsymbol{\beta}} = (\boldsymbol{X^T X})^{-1}\boldsymbol{X^T y} = \begin{bmatrix} \frac{1}{n_0} & -\frac{1}{n_0} \\ -\frac{1}{n_0} & \frac{n}{n_1 n_0} \end{bmatrix} \begin{bmatrix} n\bar{y}_{.j1} \\ n_1\bar{y}_{.11} \end{bmatrix} = \begin{bmatrix} \frac{n\bar{y}_{.j1} - n_1\bar{y}_{.11}}{n_0} \\ \frac{n\bar{y}_{.11} - n\bar{y}_{.j1}}{n_0} \end{bmatrix}.$$

Taking the estimator of the ATE $\hat{\beta}_1$ we have

$\hat{\beta}_1 = \frac{n\bar{y}_{.11} - n\bar{y}_{.j1}}{n_0} = \frac{(n_0+n_1)\bar{y}_{.11} - \sum_{i=1}^{n_0} y_{i01} - \sum_{i=1}^{n_1} y_{i11}}{n_0} = \bar{y}_{.11} - \bar{y}_{.01}.$ Result 11

Therefore, the estimator of the treatment effect $\hat{\beta}_1$ is equal to the sample mean of the intervention post scores of group 1 minus the sample mean of the intervention post scores of group 0. The same result can be derived from direct minimisation of the sum of squares. Here we have

$PS(\hat{\boldsymbol{\beta}}) = \sum_{i=1}^{n}\left(y_{ij1} - (\hat{\beta}_0 + \hat{\beta}_1 G_{ij})\right)^2$

Taking derivatives and setting to zero we have

$\frac{\partial PS}{\partial \hat{\beta}_0} = -2\sum_{i=1}^{n}\left(y_{ijk} - (\hat{\beta}_0 + \hat{\beta}_1 G_{ij})\right) = 0 \rightarrow n\hat{\beta}_0 + n_1\hat{\beta}_1 = n_0\bar{y}_{.01} + n_1\bar{y}_{.11}.$

$\frac{\partial PS}{\partial \hat{\beta}_1} = -2\sum_{i=1}^{n}\left(G_{ij}y_{ijk} - (G_{ij}\hat{\beta}_0 + \hat{\beta}_1 G_{ij}^2)\right) = 0 \rightarrow n_1\hat{\beta}_0 + n_1\hat{\beta}_1 = n_1\bar{y}_{.11}.$

Solving these two equations gives

$\hat{\beta}_0 = \bar{y}_{.01}$ and $\hat{\beta}_1 = \bar{y}_{.11} - \bar{y}_{.01}$.

ANOVA interaction model

The ANOVA interaction model can be expressed as

$y_{ijk} = \beta_0 + \beta_1 G_{ij} + \beta_2 T_{ij} + \beta_3 G_{ij} T_{ij} + \zeta_{ijk}$

Where T_{ij} is a binary time indicator ($0 =$ baseline, $1 =$ post-intervention) and β_3 is the treatment effect. For the ANOVA interaction model the design matrix $\boldsymbol{X}$ comprises four columns, the first is $\mathbf{1}'$ of length $2n$; the second column includes $2n_0$ 0's (group 0) and $2n_1$ 1s (group 1); the third includes n 0's (baseline) and n 1's (post-intervention), in the order n_0 0's, n_0 1's, n_1 0's, n_1 1's; and the fourth column is the product of the second and third columns (e.g. $2n - n_1$0's and n_1 1's). We then have

$$\boldsymbol{X^T X} = \begin{bmatrix} 2n & 2n_1 & n_1 + n_0 & n_1 \\ 2n_1 & 2n_1 & n_1 & n_1 \\ n_1 + n_0 & n_1 & n_1 + n_0 & n_1 \\ n_1 & n_1 & n_1 & n_1 \end{bmatrix}.$$

Focussing on obtaining $\hat{\beta}_3$ and calculating the determinant and required entries for the adjoint $\boldsymbol{X^T X}$ matrix we have that

$(\boldsymbol{X^T X})^{-1} = \frac{1}{n_1^4+n^2n_1^2-2n_1^3n}\begin{bmatrix} . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ n_1^2n_0 & n_1^2n-n_1n^2 & 2n_1^3-2n_1^2n & 2n^2n_1-2n_1^2n \end{bmatrix}$ which can be simplified to

$(\boldsymbol{X^T X})^{-1} = \frac{1}{n_1^2n_0^2}\begin{bmatrix} . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ n_1^2n_0 & -n_1n_0(n_1+n_0) & -2n_1^2n_0 & 2n_1n_0(n_1+n_0) \end{bmatrix}$. We also have

$$\boldsymbol{X^T y} = \begin{bmatrix} \sum_{i=1}^{n} y_{ij0} + \sum_{i=1}^{n} y_{ij1} & = n\bar{y}_{.j0} + n\bar{y}_{.j1} \\ \sum_{i=1}^{n_1} y_{i10} + \sum_{i=1}^{n_1} y_{i11} & = n_1\bar{y}_{.10} + n_1\bar{y}_{.11} \\ \sum_{i=1}^{n_0} y_{i01} + \sum_{i=1}^{n_1} y_{i11} & = n_0\bar{y}_{.01} + n_1\bar{y}_{.11} \\ \sum_{i=1}^{n_1} y_{i11} & = n_1\bar{y}_{.11} \end{bmatrix}.$$

Therefore, the estimator of the ATE $\hat{\beta}_3$ is

$\hat{\beta}_3 = \frac{n\bar{y}_{.j0}+n\bar{y}_{.j1}}{n_0} - \frac{(n_1+n_0)(n_1\bar{y}_{.10}+n_1\bar{y}_{.11})}{n_1n_0} - \frac{2(n_0\bar{y}_{.01}+n_1\bar{y}_{.11})}{n_0} + \frac{2(n_1+n_0)n_1\bar{y}_{.11}}{n_1n_0} =$

$\frac{1}{n_0}\left(\sum_{i=1}^{n} y_{ij0} - \sum_{i=1}^{n_1} y_{i10}\right) + \frac{1}{n_0}\left(\sum_{i=1}^{n} y_{ij1} - n_1\bar{y}_{.11}\right) - 2\bar{y}_{.01} + \bar{y}_{.11} - \bar{y}_{.10} = (\bar{y}_{.11} - \bar{y}_{.10}) - (\bar{y}_{.01} - \bar{y}_{.00}).$ Result 12

That is, the estimator of the treatment effect $\hat{\beta}_3$ is equal to the difference in the change in sample means across the intervention period between intervention group 1 and 0.

Deriving the above using direct minimisation of the sum of squares gives

$AI(\hat{\boldsymbol{\beta}}) = \sum_{i=1}^{n}\left(y_{ijk} - \left(\hat{\beta}_0 + \hat{\beta}_1 G_{ij} + \hat{\beta}_2 T_{ij} + \hat{\beta}_3 G_{ij}T_{ij}\right)\right)^2$

Taking derivatives and setting to zero we have

$\frac{\partial AI}{\partial \hat{\beta}_0} = -2\sum_{i=1}^{n}\left(y_{ijk} - \left(\hat{\beta}_0 + \hat{\beta}_1 G_{ij} + \hat{\beta}_2 T_{ij} + \hat{\beta}_3 G_{ij}T_{ij}\right)\right) = 0.$

$\frac{\partial AI}{\partial \hat{\beta}_1} = -2\sum_{i=1}^{n}\left(G_{ij}y_{ijk} - \left(G_{ij}\hat{\beta}_0 + \hat{\beta}_1 G_{ij}^2 + \hat{\beta}_2 G_{ij}T_{ij} + \hat{\beta}_3 G_{ij}^2T_{ij}\right)\right) = 0.$

$\frac{\partial AI}{\partial \hat{\beta}_2} = -2\sum_{i=1}^{n}\left(T_{ij}y_{ijk} - \left(T_{ij}\hat{\beta}_0 + \hat{\beta}_1 G_{ij}T_{ij} + \hat{\beta}_2 T_{ij}^2 + \hat{\beta}_3 G_{ij}T_{ij}^2\right)\right) = 0.$

$\frac{\partial AI}{\partial \hat{\beta}_3} = -2\sum_{i=1}^{n}\left(G_{ij}T_{ij}y_{ijk} - \left(G_{ij}T_{ij}\hat{\beta}_0 + \hat{\beta}_1 G_{ij}^2T_{ij} + \hat{\beta}_2 G_{ij}T_{ij}^2 + \hat{\beta}_3 G_{ij}^2T_{ij}^2\right)\right) = 0.$

This gives the following four equations

$(2n_0 + 2n_1)\hat{\beta}_0 + 2n_1\hat{\beta}_1 + (n_0+n_1)\hat{\beta}_2 + n_1\hat{\beta}_3 = n_0\bar{y}_{.00} + n_0\bar{y}_{.01} + n_1\bar{y}_{.10} + n_1\bar{y}_{.11}$

$2n_1\hat{\beta}_0 + 2n_1\hat{\beta}_1 + n_1\hat{\beta}_2 + n_1\hat{\beta}_3 = n_1\bar{y}_{.10} + n_1\bar{y}_{.11}$

$(n_0+n_1)\hat{\beta}_0 + n_1\hat{\beta}_1 + (n_0+n_1)\hat{\beta}_2 + n_1\hat{\beta}_3 = n_0\bar{y}_{.01} + n_1\bar{y}_{.11}$

$n_1\hat{\beta}_0 + n_1\hat{\beta}_1 + n_1\hat{\beta}_2 + n_1\hat{\beta}_3 = n_1\bar{y}_{.11}.$

From equation two and four we have that

$\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3 = \bar{y}_{.11}$ and $\hat{\beta}_0 + \hat{\beta}_1 = \bar{y}_{.10}$.

From equation three and one we then have

$\hat{\beta}_0 + \hat{\beta}_2 = \bar{y}_{.01}$ and $\hat{\beta}_0 = \bar{y}_{.00}$, such that

$\hat{\beta}_3 = (\bar{y}_{.11} - \bar{y}_{.01}) - (\bar{y}_{.10} - \bar{y}_{.00}).$

ANCOVA model

The ANCOVA model can be expressed as

$y_{ij1} = \beta_0 + \beta_1 G_{ij} + \beta_2 y_{ij0} + \zeta_{ij1}$

Where β_1 is the treatment effect after accounting for pre-intervention scores. For the ANCOVA model the design matrix $\boldsymbol{X}$ comprises three columns, the first is $\mathbf{1}'$, the second includes n_0 0's and n_1 1s, and the third is the baseline scores. We then have $\boldsymbol{X^T X} =$

$\begin{bmatrix} n & n_1 & n\bar{y}_{.j0} \\ n_1 & n_1 & n_1\bar{y}_{.10} \\ n\bar{y}_{.j0} & n_1\bar{y}_{.10} & \sum_{i=1}^{n} y_{ij0}^2 \end{bmatrix}$ and $(\boldsymbol{X^T X})^{-1} =$

$$\frac{1}{n_1\left(n_0\sum_{i=1}^{n} y_{ij0}^2 + 2n_1n\bar{y}_{.j0}\bar{y}_{.10} - n^2\bar{y}_{.j0}^2 - n_1n\bar{y}_{.10}^2\right)}\begin{bmatrix} n_1\left(\sum_{i=1}^{n} y_{ij0}^2 - n_1\bar{y}_{.10}^2\right) & n_1\left(n\bar{y}_{.j0}\bar{y}_{.10} - \sum_{i=1}^{n} y_{ij0}^2\right) & n_1\left(n_1\bar{y}_{.10} - n\bar{y}_{.j0}\right) \\ n_1\left(n\bar{y}_{.10}\bar{y}_{.j0} - \sum_{i=1}^{n} y_{ij0}^2\right) & n\left(\sum_{i=1}^{n} y_{ij0}^2 - n\bar{y}_{.j0}^2\right) & n_1\left(n\bar{y}_{.j0} - n\bar{y}_{.10}\right) \\ n_1\left(n_1\bar{y}_{.10} - n\bar{y}_{.j0}\right) & n_1\left(n\bar{y}_{.j0} - n\bar{y}_{.10}\right) & n_1n_0 \end{bmatrix}$$

Which can be expressed as

$$\frac{1}{n_0(S_{.00}+S_{.10})}\begin{bmatrix} \sum_{i=1}^{n} y_{ij0}^2 - n_1\bar{y}_{.10}^2 & n\bar{y}_{.j0}\bar{y}_{.10} - \sum_{i=1}^{n} y_{ij0}^2 & -n_0\bar{y}_{.00} \\ n\bar{y}_{.10}\bar{y}_{.j0} - \sum_{i=1}^{n} y_{ij0}^2 & n/n_1\left(\sum_{i=1}^{n} y_{ij0}^2 - n\bar{y}_{.j0}^2\right) & n\left(\bar{y}_{.j0} - \bar{y}_{.10}\right) \\ -n_0\bar{y}_{.00} & n\left(\bar{y}_{.j0} - \bar{y}_{.10}\right) & n_0 \end{bmatrix},$$

where $S_{.00} = \sum_{i=1}^{n_0}(y_{i00} - \bar{y}_{.00})^2$, $S_{.10} = \sum_{i=1}^{n_1}(y_{i10} - \bar{y}_{.10})^2$. We also have `

$$\boldsymbol{X^T y} = \begin{bmatrix} \sum_{i=1}^{n} y_{ij1} & = n\bar{y}_{.j1} \\ \sum_{i=1}^{n_1} y_{i11} & = n_1\bar{y}_{.11} \\ \sum_{i=1}^{n} y_{ij0}y_{ij1} & = n\bar{y}_{.j0/1} \end{bmatrix}.$$

For the ANCOVA model treatment effect estimate $\hat{\beta}_1$, we first calculate $\hat{\beta}_2$ and show that this latter expression appears in the former.
Using P10 we have that

$$\hat{\beta}_2 = \frac{(-n_0\bar{y}_{.00})n\bar{y}_{.j1} + n(\bar{y}_{.j0} - \bar{y}_{.10})n_1\bar{y}_{.11} + n_0 n\bar{y}_{.j0/1}}{n_0(S_{.00} + S_{.10})} =$$

$$\frac{-n_0^2\bar{y}_{.00}\bar{y}_{.01} - n_0n_1\bar{y}_{.00}y_{.11} + n_0n_1\bar{y}_{.00}\bar{y}_{.11} + n_1^2\bar{y}_{.10}\bar{y}_{.11} - n_0n_1\bar{y}_{.10}\bar{y}_{.11} - n_1^2\bar{y}_{.10}\bar{y}_{.11} + n_0\left(\sum_{i=1}^{n_0} y_{i00}y_{i01} + \sum_{i=1}^{n_1} y_{i10}y_{i11}\right)}{n_0(S_{.00} + S_{.10})} = \frac{S_{.00/1} + S_{.10/1}}{S_{.00} + S_{.10}},$$

where $S_{.00/1} = \sum_{i=1}^{n_0}(y_{i00} - \bar{y}_{.00})(y_{i01} - \bar{y}_{.01})$ and $S_{.10/1} = \sum_{i=1}^{n_1}(y_{i10} - \bar{y}_{.10})(y_{i11} - \bar{y}_{.11})$.
Using P10 we have that for $\hat{\beta}_1$ the treatment effect,

$$\hat{\beta}_1 = \frac{n\bar{y}_{.11}(S_{.j0}) - n\bar{y}_{.10}(S_{.j0/1}) + n\bar{y}_{.j0}S_{.j0/1} - n\bar{y}_{.j1}S_{.j0}}{n_0(S_{.00} + S_{.10})} =$$

$$\frac{\bar{y}_{.11}\left((n_0+n_1)(S_{.00}+S_{.10}) + (n_1n_0)(\bar{y}_{.00}^2 + \bar{y}_{.01}^2 - 2\bar{y}_{.00}\bar{y}_{.10})\right)}{n_0(S_{.00}+S_{.10})} -$$

$$\frac{\bar{y}_{.10}\left((n_0+n_1)(S_{.00/1}+S_{.10/1}) + n_0n_1(\bar{y}_{.00}\bar{y}_{.01} + \bar{y}_{.10}\bar{y}_{.11} - \bar{y}_{.00}\bar{y}_{.11} - \bar{y}_{.01}\bar{y}_{.10})\right)}{n_0(S_{.00}+S_{.10})} +$$

$$\frac{(n_0\bar{y}_{.00} + n_1\bar{y}_{.10})\left(S_{.00/1} + S_{.10/1} + n_0\bar{y}_{.00}\bar{y}_{.01} + n_1\bar{y}_{.10}\bar{y}_{.11}\right)}{n_0(S_{.00}+S_{.10})} -$$

$$\frac{(n_0\bar{y}_{.01} + n_1\bar{y}_{.11})(S_{.00} + S_{.10} + n_0\bar{y}_{.00}^2 + n_1\bar{y}_{.10}^2)}{n_0(S_{.00}+S_{.10})} =$$

$$(\bar{y}_{.11} - \bar{y}_{.01}) - (\bar{y}_{.10} - \bar{y}_{.00})\frac{(S_{.00/1} + S_{.10/1})}{(S_{.00} + S_{.10})} = (\bar{y}_{.11} - \bar{y}_{.01}) - (\bar{y}_{.10} - \bar{y}_{.00})\hat{\beta}_2. \quad \text{Result 13}$$

Therefore, the estimator of the treatment effect $\hat{\beta}_1$ is equal to the difference in the post-intervention sample means adjusted for by the difference in the pre-intervention sample means. We can see that if $\hat{\beta}_2$ is equal to 1 (which is reflective of the case where there is no relationship between baseline value and change score), then the estimator is the same as the ANOVA interaction case. However, where there is a relationship, we expect $\hat{\beta}_2$ to adjust accordingly.
Deriving the above using direct minimisation of the sum of squares gives

$$AC(\hat{\boldsymbol{\beta}}) = \sum_{i=1}^{n}\left(y_{ij1} - (\hat{\beta}_0 + \hat{\beta}_1G_{ij} + \hat{\beta}_2y_{ij0})\right)^2$$

Taking derivatives and setting to zero we have

$$\frac{\partial AI}{\partial\hat{\beta}_0} = -2\sum_{i=1}^{n}\left(y_{ij1} - (\hat{\beta}_0 + \hat{\beta}_1G_{ij} + \hat{\beta}_2y_{ij0})\right) = 0$$

$$\frac{\partial AI}{\partial\hat{\beta}_1} = -2\sum_{i=1}^{n}\left(G_{ij}y_{ij1} - (\hat{\beta}_0G_{ij} + \hat{\beta}_1G_{ij}^2 + \hat{\beta}_2G_{ij}y_{ij0})\right) = 0$$

$$\frac{\partial AI}{\partial\hat{\beta}_2} = -2\sum_{i=1}^{n}\left(y_{ij0}y_{ij1} - (\hat{\beta}_0y_{ij0} + \hat{\beta}_1y_{ij0}G_{ij} + \hat{\beta}_2y_{ij0}^2)\right) = 0.$$

This gives the following three equations

$$(n_0 + n_1)\hat{\beta}_0 + n_1\hat{\beta}_1 + (n_0\bar{y}_{.00} + n_1\bar{y}_{.10})\hat{\beta}_2 = n_0\bar{y}_{.01} + n_1\bar{y}_{.11}$$

$$n_1\hat{\beta}_0 + n_1\hat{\beta}_1 + n_1\bar{y}_{.10}\hat{\beta}_2 = n_1\bar{y}_{.11}$$

$$(n_0\bar{y}_{.00} + n_1\bar{y}_{.10})\hat{\beta}_0 + n_1\bar{y}_{.10}\hat{\beta}_1 + \left(\sum_{i=1}^{n_0} y_{i00}^2 + \sum_{i=1}^{n_1} y_{i10}^2\right)\hat{\beta}_2 = \sum_{i=1}^{n_0} y_{i00}y_{i01} + \sum_{i=1}^{n_1} y_{i10}y_{i11}.$$

Using the first two equations we obtain
$\bar{y}_{.11} = \hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2\bar{y}_{.10}$ and $\bar{y}_{.01} = \hat{\beta}_0 + \hat{\beta}_2\bar{y}_{.00}$, which can be rearranged to show

$$\hat{\beta}_1 = (\bar{y}_{.11} - \bar{y}_{.01}) - (\bar{y}_{.10} - \bar{y}_{.00})\hat{\beta}_2.$$

eliminating $\hat{\beta}_0$ and $\hat{\beta}_1$ from the third equation gives
$n_0\bar{y}_{.00}(\bar{y}_{.01} - \hat{\beta}_2\bar{y}_{.00}) + n_1\bar{y}_{.10}(\bar{y}_{.11} - \hat{\beta}_2\bar{y}_{.10}) + \left(\sum_{i=1}^{n_0} y_{i00}^2 + \sum_{i=1}^{n_1} y_{i10}^2\right)\hat{\beta}_2 = \sum_{i=1}^{n_0} y_{i00}y_{i01} + \sum_{i=1}^{n_1} y_{i10}y_{i11}$, which can be expressed as

$$\hat{\beta}_2 = \frac{S_{.00/1} + S_{.10/1}}{S_{.00} + S_{.10}}.$$

Appendix D: Bias and precision

We now identify bias and precision (reciprocal of the variance of the estimator) for the different regression models under our two data generating mechanisms, and we also examine conditional bias under baseline imbalance.

Post score model

The expectation and variance of our treatment effect estimator for the post score model is

$E(\hat{\beta}_1) = E(\bar{y}_{.11} - \bar{y}_{.01}) = \frac{1}{n_1}E\left(\sum_{i=1}^{n_1} y_{i11}\right) - \frac{1}{n_0}E\left(\sum_{i=1}^{n_0} y_{i01}\right) = E(y_{i11}) - E(y_{i01})$.

$\text{Var}(\hat{\boldsymbol{\beta}}) = \sigma^2(\boldsymbol{X}^T\boldsymbol{X})^{-1} = \sigma^2\begin{bmatrix} \frac{1}{n_0} & -\frac{1}{n_0} \\ -\frac{1}{n_0} & \frac{n}{n_1 n_0} \end{bmatrix}$.

Independent case

For the independent case we have

$E(y_{i11}) - E(y_{i01}) = \mu_0 + \Delta_1 - \mu_0 - \Delta_0 = \Delta_1 - \Delta_0,$ Result 14

hence the estimator is unbiased. From result 5 we have that the variance of the treatment effect estimator is

$\text{Var}(\hat{\beta}_1) = \frac{(\sigma_0^2 + v_1^2 + \delta_1^2)}{n_0} + \frac{(\sigma_0^2 + v_1^2 + \delta_1^2)}{n_1}$. Result 15

Constrained linear case

For the constrained linear case we have

$E(y_{i11}) - E(y_{i01}) = \mu_0(1+\tau) + \tilde{\Delta}_1 - \mu_0(1+\tau) - \tilde{\Delta}_0$
$= \tilde{\Delta}_1 - \tilde{\Delta}_0,$ Result 16

hence the estimator is unbiased. From result 10 we have that the variance of the treatment effect estimator is

$\text{Var}(\hat{\beta}_1) = \frac{(1+\tau)^2\sigma_0^2 + \tilde{v}_1^2 + \delta_1^2}{n_0} + \frac{(1+\tau)^2\sigma_0^2 + \tilde{v}_1^2 + \delta_1^2}{n_1}$. Result 17

We can see that in the constrained linear case if τ is negative then the precision will increase for stronger relationships with baseline value and the opposite if τ is positive.

Finally, we assess the conditional expectation where we have a baseline imbalance and implement a simple model such that $Y_{i10} - Y_{i00} = \delta$.

Independent case

For the independent case we have

$E(\hat{\beta}_1 | Y_{i10} - Y_{i00} = \delta) = E(y_{i11} - y_{i01} | Y_{i10} - Y_{i00} = \delta)$
$= E(Y_{i10} + \Delta_1 + \epsilon_{i11} - (Y_{i00} + \Delta_0 + \epsilon_{i01}) | Y_{i10} - Y_{i00} = \delta)$
$= \delta + \Delta_1 - \Delta_0,$ Result 18

hence the estimator is conditionally biased.

Constrained linear case

For the constrained linear case we have

$E(\hat{\beta}_1 | Y_{i10} - Y_{i00} = \delta) = E(y_{i11} - y_{i01} | Y_{i10} - Y_{i00} = \delta)$
$= E\left(Y_{i10} + \tilde{\Delta}_1 + \tau Y_{i10} + \epsilon_{i11} - \left(Y_{i00} + \tilde{\Delta}_0 + \tau Y_{i00} + \epsilon_{i01}\right) | Y_{i10} - Y_{i00} = \delta\right)$
$= \delta(1+\tau) + \tilde{\Delta}_1 - \tilde{\Delta}_0,$ Result 19

hence the estimator is conditionally biased.

ANOVA interaction model

The general linear model and ordinary least squares assumes that the error terms follow a multivariate normal distribution with zero correlation and constant variance. However, for the ANOVA regression model where we have repeated measures and change across time, we expect the error terms to be correlated and for variance to change across time. In practice, two generalized linear models are considered, the first assumes constant variance over the two time points (σ^2) and is what is used to fit repeated measures ANOVA in most software, referred to more broadly as compound symmetry. This structure can be relaxed, however, and variance allowed to change across time (σ_0^2, σ_1^2). Wan (2021) shows that using generalized least squares and P13, the estimator of the ATE $\hat{\beta}_3$ remains unchanged from ordinary least squares (Result 12). However, from P14, precision changes such that

$\text{Var}(\hat{\beta}_3) = \left(\frac{1}{n_0} + \frac{1}{n_1}\right)\left(\text{Var}(y_{ij0}) + \text{Var}(y_{ij1}) - 2\rho\sqrt{\text{Var}(y_{ij0})\text{Var}(y_{ij1})}\right)$. Result 20

The relationship between compound symmetry and the more relaxed structure is summarised by $\sigma^2 = \frac{n_0\sigma_0^2 + n_1\sigma_1^2}{n}$.

We can now assess bias and precision of this ANOVA estimator under our two data generating mechanisms. For bias we have

$E(\hat{\beta}_3) = E\left((\bar{y}_{.11} - \bar{y}_{.10}) - (\bar{y}_{.01} - \bar{y}_{.00})\right)$
$= \frac{1}{n_1}E\left(\sum_{i=1}^{n_1} y_{i11} - \sum_{i=1}^{n_1} y_{i10}\right) - \frac{1}{n_0}E\left(\sum_{i=1}^{n_0} y_{i01} - \sum_{i=1}^{n_0} y_{i00}\right)$

$$= E(y_{i11}) - E(y_{i10}) - E(y_{i01}) + E(y_{i00}).$$

Independent case
For the independent case we have

$$E(y_{i11}) - E(y_{i10}) - E(y_{i01}) + E(y_{i00}) = \mu_0 + \Delta_1 - \mu_0 + \Delta_0 - \mu_0 + \mu_0$$
$$= \Delta_1 - \Delta_0, \qquad \text{Result 21}$$

hence the estimator is unbiased. We also have that the variance of the treatment effect estimator is

$$\text{Var}(\hat{\beta}_3) = \left(\frac{1}{n_0} + \frac{1}{n_1}\right)(\sigma_0^2 + \delta_0^2 + \sigma_0^2 + \nu_1^2 + \delta_1^2 - 2\sigma_0^2)$$
$$= \frac{(\delta_0^2+\nu_1^2+\delta_1^2)}{n_0} + \frac{(\delta_0^2+\nu_1^2+\delta_1^2)}{n_1}. \qquad \text{Result 22}$$

Constrained linear case

For the constrained linear case we have

$$E(y_{i11}) - E(y_{i10}) - E(y_{i01}) + E(y_{i00}) = \mu_0(1+\tau) + \widetilde{\Delta}_1 - \mu_0(1+\tau) - \widetilde{\Delta}_0 - \mu_0 + \mu_0$$
$$= \widetilde{\Delta}_1 - \widetilde{\Delta}_0, \qquad \text{Result 23}$$

hence the estimator is unbiased. We also have that the variance of the treatment effect estimator is

$$\text{Var}(\hat{\beta}_3) = \left(\frac{1}{n_0} + \frac{1}{n_1}\right)\left(\sigma_0^2 + \delta_0^2 + (1+\tau)^2\sigma_0^2 + \tilde{\nu}_1^2 + \delta_1^2 - 2\sigma_0^2(1+\tau)\right)$$
$$= \frac{(\tau^2\sigma_0^2+\delta_0^2+\tilde{\nu}_1^2+\delta_1^2)}{n_0} + \frac{(\tau^2\sigma_0^2+\delta_0^2+\tilde{\nu}_1^2+\delta_1^2)}{n_1}. \qquad \text{Result 24}$$

Comparing results 22 and 24 with results 15 and 17, we can also see that as long as $\delta_0^2 < \sigma_0^2$, the precision using the ANOVA interaction model is greater than the precision using the post score model.

As a side note we can see that if we conduct the post score regression model but instead use change scores from baseline to post-intervention, then from result 9 we will have

$$\hat{\beta}_1 = (\bar{y}_{.11} - \bar{y}_{.10}) - (\bar{y}_{.01} - \bar{y}_{.00}).$$

This is the same estimator of the treatment effect as the ANOVA interaction model. Also from the post score regression model we have

$$\text{Var}(\hat{\boldsymbol{\beta}}) = \sigma^2(\boldsymbol{X}^T\boldsymbol{X})^{-1} = \sigma^2\begin{bmatrix} \frac{1}{n_0} & -\frac{1}{n_0} \\ -\frac{1}{n_0} & \frac{n}{n_1 n_0} \end{bmatrix}.$$

Given σ^2 for change scores is $\text{Var}(y_{ij0}) + \text{Var}(y_{ij1}) - 2\rho\sqrt{\text{Var}(y_{ij0})\text{Var}(y_{ij1})}$, we will obtain the same precision as the ANOVA interaction model. We can see therefore, that under our homogeneity cases we will make the same inferences using a simple regression (or independent t-test) on change scores, as we will using the ANOVA interaction model.

Finally, we assess the conditional expectation for the ANOVA interaction model where we have a baseline imbalance and implement a simple model such that $Y_{i10} - Y_{i00} = \delta$.

Independent case
For the independent case we have

$$E(\hat{\beta}_3 | \, Y_{i10} - Y_{i00} = \delta) = E(y_{i11} - y_{i10} - y_{i01} + y_{i00} | Y_{i10} - Y_{i00} = \delta)$$
$$= E(Y_{i10} + \Delta_1 + \epsilon_{i11} - (Y_{i10} + \epsilon_{i10}) - (Y_{i00} + \Delta_0 + \epsilon_{i01}) + Y_{i00} + \epsilon_{i00} | Y_{i10} - Y_{i00} = \delta)$$
$$= \Delta_1 - \Delta_0, \qquad \text{Result 25}$$

hence the estimator is conditionally unbiased.

Constrained linear case
For the constrained linear case we have

$$(\hat{\beta}_3 | \, Y_{i10} - Y_{i00} = \delta) = E(y_{i11} - y_{i10} - y_{i01} + y_{i00} | Y_{i10} - Y_{i00} = \delta)$$
$$= E\left(Y_{i10} + \widetilde{\Delta}_1 + \tau Y_{i10} + \epsilon_{i11} - (Y_{i10} + \epsilon_{i10}) - \left(Y_{i00} + \widetilde{\Delta}_0 + \tau Y_{i00} + \epsilon_{i01}\right) + Y_{i00} + \epsilon_{i00} | Y_{i10} - Y_{i00} = \delta\right)$$
$$= \tau\delta + \widetilde{\Delta}_1 - \widetilde{\Delta}_0, \qquad \text{Result 26}$$

hence the estimator is conditionally biased.

ANCOVA Model
For deriving the expectation and variance of our estimator, we note when using ordinary least squares with the ANCOVA model we assume that baseline scores y_{ij0} are fixed Wan (2021). The conditional expectation of our estimator is

$$E(\hat{\beta}_1 | y_{ij0}) = E(\bar{y}_{.11} - \bar{y}_{.01} - (\bar{y}_{.10} - \bar{y}_{.00})\hat{\beta}_2 | y_{ij0})$$
$$= \frac{1}{n_1}E\left(\sum_{i=1}^{n_1} y_{i11} \,|y_{i10}\right) - \frac{1}{n_0}E\left(\sum_{i=1}^{n_0} y_{i01} \,|y_{i00}\right) - (\bar{y}_{.10} - \bar{y}_{.00})E(\hat{\beta}_2 | y_{ij0}).$$

The conditional expectation $E(\hat{\beta}_2 | y_{ij0})$ is given by

$$E(\hat{\beta}_2|y_{ij0}) = \frac{1}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2} E\left(\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})(y_{i01}-\bar{y}_{.01})+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})(y_{i11}-\bar{y}_{.11})|y_{ij0}\right).$$

For context we calculate expectations for both true and observed baseline values (i.e. we replace our observed baseline values with true values). From P9 we have

$$E(y_{ij1}|Y_{ij0}) = E(y_{ij1}) + \rho_{y_{ij1},Y_{ij0}}\left(\frac{\sqrt{\text{Var}(y_{ij1})}}{\sqrt{\text{Var}(Y_{ij0})}}\right)\left(Y_{ij0}-E(Y_{ij0})\right)$$

Independent case

In the independent case we have

$$E(y_{ij1}|Y_{ij0}) = \mu_0 + \Delta_j + \rho_{y_{ij1},Y_{ij0}}\left(\frac{\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}{\sigma_0}\right)(Y_{ij0}-\mu_0).$$

We also have that

$$\begin{aligned}\text{Corr}(Y_{ij0},y_{ij1}) &= \frac{E(Y_{ij0}y_{ij1})-\mu_0\mu_{j1}}{\sqrt{\text{Var}(Y_{ij0})}\sqrt{\text{Var}(y_{ij1})}}\\ &= \frac{E\left(Y_{ij0}(Y_{ij0}+\Delta_j+\xi_{ij1}+\epsilon_{ij1})\right)-\mu_0(\mu_0+\Delta_j)}{\sigma_0\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}\\ &= \frac{\sigma_0^2+\mu_0^2+\mu_0\Delta_j-\mu_0(\mu_0+\Delta_j)}{\sigma_0\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}\\ &= \frac{\sigma_0}{\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}.\end{aligned}$$

Hence

$$\begin{aligned}E(y_{ij1}|Y_{ij0}) &= \mu_0 + \Delta_j + \frac{\sigma_0}{\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}\left(\frac{\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}{\sigma_0}\right)(Y_{ij0}-\mu_0)\\ &= Y_{ij0}+\Delta_j.\end{aligned}$$

In contrast and using Result 2 we have

$$\begin{aligned}E(y_{ij1}|y_{ij0}) &= \mu_0 + \Delta_j + \frac{1}{\sqrt{1+\delta_0^2/\sigma_0^2}\sqrt{1+\nu_1^2/\sigma_0^2+\delta_1^2/\sigma_0^2}}\left(\frac{\sqrt{\sigma_0^2+\nu_1^2+\delta_1^2}}{\sqrt{\sigma_0^2+\delta_0^2}}\right)(y_{ij0}-\mu_0)\\ &= \mu_0+\Delta_j+\frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}(y_{ij0}-\mu_0).\end{aligned}$$

To obtain expressions with $\bar{y}_{.j1}$ and using P15 and P16 we note that $\text{Cov}\left(X,\sum_{i=1}^{n}\frac{1}{n}Y_i\right)=\sum_{i=1}^{n}\frac{1}{n}\text{Cov}(X,Y_i)$ and $\text{Var}\left(\frac{1}{n}\sum_{i=1}^{n}Y_i\right)=\sum_{i=1}^{n}\frac{1}{n^2}\text{Var}(Y_i)+\frac{2}{n^2}\sum_{i<j}\text{Cov}(Y_i,Y_j)$. For the independent case therefore, we have $\text{Cov}\left(Y_{ij0},\sum_{k=1}^{n}\frac{1}{n}y_{ij1k}\right)=\text{Cov}(Y_{ij0},y_{ij1})$, $\text{Cov}(y_{ij1},y_{ij1'})=\sigma_0^2$ and for $\text{Var}(\bar{y}_{.j1})$ we will have $n(n-1)/2$ covariances to sum and so $\text{Var}(\bar{y}_{.j1})=\frac{n\sigma_0^2+\nu_1^2+\delta_1^2}{n}$.

We therefore have that

$$\begin{aligned}E(\bar{y}_{.j1}|Y_{ij0}) &= \mu_0+\Delta_j+\frac{\sigma_0^2}{\sigma_0\sqrt{\frac{n\sigma_0^2+\nu_1^2+\delta_1^2}{n}}}\left(\frac{\sqrt{\frac{n\sigma_0^2+\nu_1^2+\delta_1^2}{n}}}{\sigma_0}\right)(Y_{ij0}-\mu_0)\\ &= Y_{ij0}+\Delta_j.\end{aligned}$$

For observed scores we have that $\text{Cov}\left(y_{ij0},\sum_{k=1}^{n}\frac{1}{n}y_{ij1k}\right)=\text{Cov}(y_{ij0},y_{ij1})$, hence from result 2 we have

$$\begin{aligned}E(\bar{y}_{ij1.}|Y_{ij0}) &= \mu_0+\Delta_j+\frac{\sigma_0^2}{\sqrt{\sigma_0^2+\delta_0^2}\sqrt{\frac{n\sigma_0^2+\nu_1^2+\delta_1^2}{n}}}\left(\frac{\sqrt{\frac{n\sigma_0^2+\nu_1^2+\delta_1^2}{n}}}{\sqrt{\sigma_0^2+\delta_0^2}}\right)(Y_{ij0}-\mu_0)\\ &= \mu_0+\Delta_j+\frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}(y_{ij0}-\mu_0).\end{aligned}$$

And so, when replacing observed baseline values with the true baseline values and replacing $E(\bar{y}_{ij1}|Y_{ij0})=\bar{Y}_{ij0}+\Delta_j$ we have

$$\begin{aligned}E(\hat{\beta}_2|Y_{ij0}) &= \frac{1}{\sum_{i=1}^{n_0}(Y_{i00}-\bar{Y}_{.00})^2+\sum_{i=1}^{n_1}(Y_{i10}-\bar{Y}_{.10})^2}E\left(\sum_{i=1}^{n_0}(Y_{i00}-\bar{Y}_{.00})(y_{i01}-\bar{y}_{.01})+\sum_{i=1}^{n_1}(Y_{i10}-\bar{Y}_{.10})(y_{i11}-\bar{y}_{.11})|Y_{ij0}\right)\\ &= \frac{1}{\sum_{i=1}^{n_0}(Y_{i00}-\bar{Y}_{.00})^2+\sum_{i=1}^{n_1}(Y_{i10}-\bar{Y}_{.10})^2}\sum_{i=1}^{n_0}(Y_{i00}-\bar{Y}_{.00})(Y_{i00}+\Delta_0-\bar{Y}_{.00}-\Delta_0)+\sum_{i=1}^{n_1}(Y_{i10}-\bar{Y}_{.10})(Y_{i01}+\Delta_1-\bar{Y}_{.01}-\Delta_1)\end{aligned}$$

$= 1.$

In contrast, when using the observed baseline values and replacing $E(\bar{y}_{ij1}|y_{ij0}) = \bar{y}_{ij0} + \Delta_j$ we have

$$E(\hat{\beta}_2|y_{ij0}) = \frac{1}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2} E\left(\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})(y_{i01}-\bar{y}_{.01}) + \sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})(y_{i11}-\bar{y}_{.11})|y_{ij0}\right)$$
$$= \frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}.$$

Finally, combining the results above we have for true baseline values

$$E(\hat{\beta}_1|Y_{ij0}) = \frac{1}{n_1}E\left(\sum_{i=1}^{n_1} y_{i11}|Y_{i10}\right) - \frac{1}{n_0}E\left(\sum_{i=1}^{n_0} y_{i01}|Y_{i00}\right) - (\bar{y}_{.10}-\bar{y}_{.00})E(\hat{\beta}_2|Y_{ij0})$$
$$= \bar{Y}_{.10} + \Delta_1 - \bar{Y}_{.00} - \Delta_0 - \bar{Y}_{.10} + \bar{Y}_{.00}$$
$$= \Delta_1 - \Delta_0, \qquad \text{Result 27}$$

hence the estimator is unbiased. For observed baseline values we have

$$E(\hat{\beta}_1|y_{ij0}) = \frac{1}{n_1}E\left(\sum_{i=1}^{n_1} y_{i11}|y_{i10}\right) - \frac{1}{n_0}E\left(\sum_{i=1}^{n_0} y_{i01}|y_{i00}\right) - (\bar{y}_{.10}-\bar{y}_{.00})E(\hat{\beta}_2|y_{ij0})$$
$$= \mu_0 + \Delta_1 + \frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}(\bar{y}_{.10}-\mu_0) - \left(\mu_0 + \Delta_0 + \frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}(\bar{y}_{.00}-\mu_0)\right) - (\bar{y}_{.10}-\bar{y}_{.00})\frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}$$
$$= \Delta_1 - \Delta_0, \qquad \text{Result 28}$$

hence the estimator is unbiased.

These results show that whilst we obtain different estimates $\hat{\beta}_2$ with and without measurement error, we obtain unbiased treatment effect estimates both with and without measurement error. Repeating the same process for the constrained linear case we have

$E(\hat{\beta}_2|Y_{ij0}) = 1 + \tau$ and $E(\hat{\beta}_2|y_{ij0}) = \frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}(1+\tau)$.

And again, both with and without measurement error in the constrained linear case the treatment estimator is unbiased (Result 29 and Result 30).

For assessing potential bias where we have a baseline imbalance such that $Y_{i10} - Y_{i00} = \delta$, we note that in the independent case with no measurement error our ANCOVA treatment estimator will be $(\bar{y}_{.11} - \bar{y}_{.10}) - (\bar{y}_{.01} - \bar{y}_{.00})$. This is the same as the treatment estimator for the ANOVA interaction model, which was conditionally unbiased, hence our ANCOVA estimator will also be unbiased for baseline imbalance. However, where we have measurement error we have

$$E(\hat{\beta}_1|\, Y_{i10} - Y_{i00} = \delta) = E\left(y_{i11} - y_{i01} - (y_{i10} - y_{i00})\hat{\beta}_2|Y_{i10} - Y_{i00} = \delta\right)$$
$$= E\left(Y_{i10} + \Delta_1 + \epsilon_{i11} - (Y_{i00} + \Delta_0 + \epsilon_{i01}) - (y_{i10} - y_{i00})\hat{\beta}_2|Y_{i10} - Y_{i00} = \delta\right)$$
$$= \Delta_1 - \Delta_0 + \left(1 - \frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}\right)\delta, \qquad \text{Result 31}$$

hence the estimator is conditionally biased.

Similarly, for the constrained linear case with no measurement error, we note that the first part of our ANCOVA treatment estimator $(\bar{y}_{.11} - \bar{y}_{.01})$ is the same as our post score model, which exhibited a bias of $\delta(1+\tau)$ where we had a baseline imbalance. We also note that the second part our ANCOVA treatment estimator is $-(\bar{y}_{.10} - \bar{y}_{.00})\hat{\beta}_2$. We see that given our baseline imbalance, we expect $\bar{y}_{.10} - \bar{y}_{.00} = \delta$. We also note that for the constrained linear case $E(\hat{\beta}_2|Y_{ij0}) = 1 + \tau$. Hence, where we have baseline imbalance such that $Y_{i10} - Y_{i00} = \delta$, then the expectation is that our ANCOVA treatment estimator with no measurement error will equal $\delta(1+\tau) + \tilde{\Delta}_1 - \tilde{\Delta}_0 - \delta(1+\tau) = \tilde{\Delta}_1 - \tilde{\Delta}_0$, and hence is conditionally unbiased. In contrast, here we have measurement error, we have

$$E(\hat{\beta}_1|\, Y_{i10} - Y_{i00} = \delta) = E\left(y_{i11} - y_{i01} - (y_{i10} - y_{i00})\hat{\beta}_2|Y_{i10} - Y_{i00} = \delta\right)$$
$$= E\left(Y_{i10} + \tilde{\Delta}_1 + \tau Y_{i10} + \epsilon_{i11} - (Y_{i00} + \tilde{\Delta}_0 + \tau Y_{i00} + \epsilon_{i01}) - (y_{i10} - y_{i00})\hat{\beta}_2|Y_{i10} - Y_{i00} = \delta\right)$$
$$= \tilde{\Delta}_1 - \tilde{\Delta}_0 + (1+\tau)\left(1 - \frac{\sigma_0^2}{\sigma_0^2+\delta_0^2}\right)\delta, \qquad \text{Result 32}$$

hence the estimator is conditionally biased.

We can see that as measurement error of baseline values reduces, or the relative magnitude of measurement error relative to variation in true baseline values reduces, the bias of the ANCOVA treatment estimator under baseline imbalance will reduce approaching no bias.

To assess precision of the ANCOVA we obtain an expression for $\mathrm{Var}(\hat{\beta}_1|y_{ij0})$ and note that the $\hat{\beta}_1$ entry of the matrix $(\boldsymbol{X}^T\boldsymbol{X})^{-1}$ can be expressed as $\frac{1}{n_0} + \frac{1}{n_1} + \frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}$.

We also have from P12 that $\mathrm{Var}(y_{ij1}|y_{ij0}) = \mathrm{Var}(y_{ij1})(1-\rho^2)$, where ρ^2 is the correlation between y_{ij1} and y_{ij0}.

In the independent case and using Result 2 we have that

$$\mathrm{Var}(\hat{\beta}_1|y_{ij0}) = \left(\frac{1}{n_0} + \frac{1}{n_1} + \frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}\right)\left((\sigma_0^2 + v_1^2 + \delta_1^2)\left(1 - \frac{\sigma_0^4}{(\sigma_0^2+\delta_0^2)(\sigma_0^2+v_1^2+\delta_1^2)}\right)\right)$$
$$= \left(\frac{1}{n_0} + \frac{1}{n_1} + \frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}\right)\left((\sigma_0^2 + v_1^2 + \delta_1^2) - \frac{\sigma_0^2}{(1+\delta_0^2/\sigma_0^2)}\right). \qquad \text{Result 33}$$

In the constrained linear case and using Result 7 we have that

$$\begin{aligned}\mathrm{Var}(\hat{\beta}_1|y_{ij0}) &= \left(\frac{1}{n_0}+\frac{1}{n_1}+\frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}\right)\left(((1+\tau)^2\sigma_0^2+\tilde{\nu}_1^2+\delta_1^2)\left(1-\frac{(1+\tau)^2\sigma_0^4}{(\sigma_0^2+\delta_0^2)((1+\tau)^2\sigma_0^2+\tilde{\nu}_1^2+\delta_1^2)}\right)\right)\\ &= \left(\frac{1}{n_0}+\frac{1}{n_1}+\frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}\right)\left((1+\tau)^2\sigma_0^2+\tilde{\nu}_1^2+\delta_1^2-\frac{(1+\tau)^2\sigma_0^2}{(1+\delta_0^2/\sigma_0^2)}\right).\end{aligned}$$

Result 34

Appendix E: Check on derived results

```
# This appendix checks the results presented in Appendix A-D, using R Code to simulate data according to the relevant data generating mechanisms and calculate various summary results.

library(nlme)

# Result 1
set.seed(123)
Y0 = rnorm(1000000,100,10)
Y1 = Y0 + 15 + rnorm(1000000,0,5)

round(cor(Y0,Y1),3)
# 0.894
round(1/sqrt(1+(25/100)),3)
# 0.894
# Matches result presented

# Result 2
set.seed(321)
y0 = Y0 + rnorm(1000000,0,2)
y1 = Y1 + rnorm(1000000,0,4)

round(cor(y0,y1),3)
# 0.826
round(1/(sqrt(1+(4/100))*sqrt(1+(25/100)+(16/100))),3)
# 0.826
# Matches result presented

# Result 3
round(cor(Y0,(Y1-Y0)),2)
# 0
# Matches result presented

# Result 6
set.seed(123)
Y0 = rnorm(1000000,100,10)
Y1A = Y0 + 15 + -0.4*Y0 + rnorm(1000000,0,5)

round(cor(Y0,Y1A),3)
# 0.768
round((1-0.4)/sqrt((1-0.4)^2+(25/100)),3)
# 0.768
# Matches result presented

# Result 7
set.seed(321)
y0 = Y0 + rnorm(1000000,0,2)
y1A = Y1A + rnorm(1000000,0,4)

round(cor(y0,y1A),3)
# 0.67
round((1-0.4)/(sqrt(1+(4/100))*sqrt((1-0.4)^2+(25/100)+(16/100))),3)
# 0.67
# Matches result presented

# Result 8
round(cor(Y0,(Y1A-Y0)),2)
# -0.62
round(-0.4/sqrt(0.4^2+(25/100)),2)
# -0.62
# Matches result presented

# Result 9
set.seed(123)
XPost = cbind(rep(1,10000),c(rep(0,2500),rep(1,7500)))
YPost = 20 + XPost[,2]*10 + rnorm(10000)

round(solve(t(XPost)%*%XPost)%*%t(XPost)%*%YPost,4)[2,1]
# 9.9827
```

```
round(mean(YPost[2501:10000])-mean(YPost[1:2500]),4)
# 9.9827
# Matches result presented

# Result 12
set.seed(123)
XANOVA = cbind(rep(1,20000),c(rep(0,5000),rep(1,15000)),
        c(rep(0,2500),rep(1,2500),rep(0,7500),rep(1,7500)),
        c(rep(0,12500),rep(1,7500)))
YANOVA = 20 + XANOVA[,2]*10 + XANOVA[,3]*15 + XANOVA[,4]*5 + rnorm(20000)

round(solve(t(XANOVA)%*%XANOVA)%*%t(XANOVA)%*%YANOVA,4)[4,1]
# 5.0096
round((mean(YANOVA[12501:20000])-mean(YANOVA[5001:12500]))-
    (mean(YANOVA[2501:5000])-mean(YANOVA[1:2500])),4)
# 5.0096
# Matches result presented

# Result 13
set.seed(123)
Y0ANCOVA = rnorm(10000,100,10)
XANCOVA = cbind(rep(1,10000),c(rep(0,2500),rep(1,7500)),Y0ANCOVA)
Y1ANCOVA = 20 + XANCOVA[,2]*10 -0.3*Y0ANCOVA + rnorm(10000)

round(solve(t(XANCOVA)%*%XANCOVA)%*%t(XANCOVA)%*%Y1ANCOVA,4)[2,1]
# 9.9812
round(((mean(Y1ANCOVA[2501:10000])-mean(Y1ANCOVA[1:2500])) -
    ((mean(Y0ANCOVA[2501:10000])-mean(Y0ANCOVA[1:2500]))*
    (solve(t(XANCOVA)%*%XANCOVA)%*%t(XANCOVA)%*%Y1ANCOVA)[[3,1]])),4)
# 9.9812
# Matches result presented


# Parameters for models to check Result 14 onward
mu = 100
sigma = 10
nu = 5
delta0 = 6
delta1 = 4
n0 = 1000
n1 = 1000
Delta1 = 15
Delta0 = 10
tau = -0.3
delta = 5

# Result 14 and Result 15
PostScoreEstimator = c(NULL)
PostScoreVar = (sigma^2 + nu^2 + delta1^2)/n0 + (sigma^2 + nu^2 + delta1^2)/n1
PostScoreEstimatorCI = c(NULL)
set.seed(123)
for(i in 1:10000){
yPost = rnorm(n0+n1,mu,sigma) + c(rep(Delta0,n0),rep(Delta1,n1)) +
  rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
PostScoreEstimator[i] = mean(yPost[(n0+1):(n0+n1)])-mean(yPost[1:n0])
PostScoreEstimatorCI[i] = PostScoreEstimator[i]-(1.96*sqrt(PostScoreVar))< Delta1-Delta0 &
  PostScoreEstimator[i]+(1.96*sqrt(PostScoreVar))>Delta1-Delta0}

# Bias
round(mean(PostScoreEstimator)-5,2)
# 0
# Matches result presented

# Variance of estimator
round(var(PostScoreEstimator),2)
# 0.28
round(PostScoreVar,2)
# 0.28
# Matches result presented
```

```
#95%CI
round(mean(PostScoreEstimatorCI),2)
# 0.95
# Matches result presented

# Result 16 and Result 17
PostScoreEstimatorCL = c(NULL)
PostScoreVarCL = (((1+tau)^2)*sigma^2 + nu^2 + delta1^2)/n0 + (((1+tau)^2)*sigma^2 + nu^2 + delta1^2)/n1
PostScoreEstimatorCICL = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  yPost = YPre + tau*YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  PostScoreEstimatorCL[i] = mean(yPost[(n0+1):(n0+n1)])-mean(yPost[1:n0])
  PostScoreEstimatorCICL[i] = PostScoreEstimatorCL[i]-(1.96*sqrt(PostScoreVarCL))< Delta1-Delta0 &
    PostScoreEstimatorCL[i]+(1.96*sqrt(PostScoreVarCL))>Delta1-Delta0}

# Bias
round(mean(PostScoreEstimatorCL)-5,2)
# 0
# Matches result presented

# Variance of estimator
round(var(PostScoreEstimatorCL),2)
# 0.18
round(PostScoreVarCL,2)
# 0.18
# Matches result presented

#95%CI
round(mean(PostScoreEstimatorCICL),2)
# 0.95
# Matches result presented

# Result 18
set.seed(123)
PostScoreEstimatorIMB = c(NULL)
for(i in 1:10000){
  YPre0 = rnorm(n0,mu,sigma)
  Ypre1 = YPre0 + delta
  yPost = c(YPre0,Ypre1) + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  PostScoreEstimatorIMB[i]=mean(yPost[(n0+1):(n0+n1)])-mean(yPost[1:n0])}

# Bias
round(mean(PostScoreEstimatorIMB)-5,2)
# 5
# Matches result presented

# Result 19
set.seed(123)
PostScoreEstimatorIMBCL = c(NULL)
for(i in 1:10000){
  YPre0 = rnorm(n0,mu,sigma)
  Ypre1 = YPre0 + delta
  yPost = c(YPre0,Ypre1) + tau*c(YPre0,Ypre1) + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  PostScoreEstimatorIMBCL[i]=mean(yPost[(n0+1):(n0+n1)])-mean(yPost[1:n0])}

# Bias
round(mean(PostScoreEstimatorIMBCL)-5,2)
# 3.5
delta*(1+tau)
# 3.5
# Matches result presented


# Result 21 and Result 22
ANOVAEstimator = c(NULL)
```

```
ANOVAVar = (delta0^2 + nu^2 + delta1^2)/n0 + (delta0^2 + nu^2 + delta1^2)/n1
ANOVAEstimatorCI = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  yPre = YPre + rnorm(n0+n1,0,delta0)
  yPost = YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
    ANOVAEstimator[i] = (mean(yPost[(n0+1):(n0+n1)])-mean(yPre[(n0+1):(n0+n1)]))-
                    (mean(yPost[1:n0])-mean(yPre[1:n0]))
  ANOVAEstimatorCI[i] = ANOVAEstimator[i]-(1.96*sqrt(ANOVAVar))< Delta1-Delta0 &
    ANOVAEstimator[i]+(1.96*sqrt(ANOVAVar))>Delta1-Delta0}

# Bias
round(mean(ANOVAEstimator)-5,1)
# 0
# Matches result presented

# Variance of estimator
round(var(ANOVAEstimator),2)
# 0.15
round(ANOVAVar,2)
# 0.15
# Matches result presented

#95%CI
round(mean(ANOVAEstimatorCI),2)
# 0.95
# Matches result presented


# Result 23 and Result 24
ANOVAEstimatorCL = c(NULL)
ANOVAVarCL = ((tau^2)*sigma^2 + delta0^2 + nu^2 + delta1^2)/n0 + ((tau^2)*sigma^2+ delta0^2 + nu^2 + delta1^2)/n1
ANOVAEstimatorCICL = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  yPre = YPre + rnorm(n0+n1,0,delta0)
  yPost = YPre + tau*YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANOVAEstimatorCL[i] = (mean(yPost[(n0+1):(n0+n1)])-mean(yPre[(n0+1):(n0+n1)]))-
    (mean(yPost[1:n0])-mean(yPre[1:n0]))
  ANOVAEstimatorCICL[i] = ANOVAEstimatorCL[i]-(1.96*sqrt(ANOVAVarCL))< Delta1-Delta0 &
    ANOVAEstimatorCL[i]+(1.96*sqrt(ANOVAVarCL))>Delta1-Delta0}

# Bias
round(mean(ANOVAEstimatorCL)-5,1)
# 0
# Matches result presented

# Variance of estimator
round(var(ANOVAEstimatorCL),2)
# 0.17
round(ANOVAVarCL,2)
# 0.17
# Matches result presented

#95%CI
round(mean(ANOVAEstimatorCICL),2)
# 0.95
# Matches result presented


# Comparison with change scores
ChangeScoreEstimator = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  ypre = YPre + rnorm(n0+n1,0,delta0)
```

```
  yPost = YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ChangeScoreEstimator[i] = mean(yPost[(n0+1):(n0+n1)]-ypre[(n0+1):(n0+n1)]) -
    mean(yPost[1:n0]-ypre[1:n0])}

round(var(ChangeScoreEstimator),2)
# 0.15
# Matches Variance of ANOVA estimator

ChangeScoreEstimatorCL = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  ypre = YPre + rnorm(n0+n1,0,delta0)
  yPost = YPre + tau*YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ChangeScoreEstimatorCL[i] = mean(yPost[(n0+1):(n0+n1)]-ypre[(n0+1):(n0+n1)]) -
    mean(yPost[1:n0]-ypre[1:n0])}

round(var(ChangeScoreEstimatorCL),2)
# 0.17
# Matches Variance of ANOVA estimator


# Result 25
set.seed(123)
ANOVAEstimatorIMB = c(NULL)
for(i in 1:10000){
  YPre0 = rnorm(n0,mu,sigma)
  Ypre1 = YPre0 + delta
  ypre = c(YPre0,Ypre1) + rnorm((n0+n1),0,delta0)
  yPost = c(YPre0,Ypre1) + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANOVAEstimatorIMB[i]=mean(yPost[(n0+1):(n0+n1)]-ypre[(n0+1):(n0+n1)]) -
    mean(yPost[1:n0]-ypre[1:n0])}

# Bias
round(mean(ANOVAEstimatorIMB)-5,2)
# 0
# Matches result presented


# Result 26
set.seed(123)
ANOVAEstimatorIMBCL = c(NULL)
for(i in 1:10000){
  YPre0 = rnorm(n0,mu,sigma)
  Ypre1 = YPre0 + delta
  ypre = c(YPre0,Ypre1) + rnorm((n0+n1),0,delta0)
  yPost = c(YPre0,Ypre1) + tau*c(YPre0,Ypre1) + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANOVAEstimatorIMBCL[i]=mean(yPost[(n0+1):(n0+n1)]-ypre[(n0+1):(n0+n1)]) -
    mean(yPost[1:n0]-ypre[1:n0])}

# Bias
round(mean(ANOVAEstimatorIMBCL)-5,2)
# -1.5
tau*delta
# -1.5
# Matches result presented


# Result 27, Result 28 and Result 33
ANCOVAEstimatorB2True = c(NULL)
ANCOVAEstimatorB2Obs = c(NULL)
ANCOVAEstimatorB1True = c(NULL)
ANCOVAEstimatorB1Obs = c(NULL)
ANCOVAEstimatorB1CI = c(NULL)
ANCOVAVar = c(NULL)
set.seed(123)
```

```
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  yPre = YPre + rnorm(n0+n1,0,delta0)
  yPost = YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANCOVADF = data.frame(YPre = YPre, yPre=yPre,yPost=yPost,Group=c(rep("0",n0),rep("1",n1)))
  ANCOVAEstimatorB1True[i]=summary(lm(yPost~YPre+Group,data=ANCOVADF))$coefficients[[3,1]]
  ANCOVAEstimatorB1Obs[i]=summary(lm(yPost~yPre+Group,data=ANCOVADF))$coefficients[[3,1]]
  ANCOVAEstimatorB2True[i]=summary(lm(yPost~YPre+Group,data=ANCOVADF))$coefficients[[2,1]]
  ANCOVAEstimatorB2Obs[i]=summary(lm(yPost~yPre+Group,data=ANCOVADF))$coefficients[[2,1]]
  ANCOVAVar[i] = (1/n0 + 1/n1 +
    (((mean(yPre[(n0+1):(n0+n1)])-mean(yPre[1:n0]))^2)/
    (sum((yPre[(n0+1):(n0+n1)]-mean(yPre[(n0+1):(n0+n1)]))^2)+
    sum((yPre[1:n0]-mean(yPre[1:n0]))^2))))*
    (sigma^2 + nu^2 + delta1^2 - ((sigma^2)/(1+((delta0^2)/sigma^2))))
  ANCOVAEstimatorB1CI[i] = ANCOVAEstimatorB1Obs[i]-(1.96*sqrt(ANCOVAVar[i]))< Delta1-Delta0 &
    ANCOVAEstimatorB1Obs[i]+(1.96*sqrt(ANCOVAVar[i]))>Delta1-Delta0}

# B2 estimator no measurement error and measurement error
round(mean(ANCOVAEstimatorB2True),2)
# 1
# Matches result presented

round(mean(ANCOVAEstimatorB2Obs),2)
# 0.74
round(sigma^2/(sigma^2+delta0^2),2)
# 0.74
# Matches result presented

# Bias in B1 estimator no measurement error and measurement error
round(mean(ANCOVAEstimatorB1True)-5,1)
# 0
# Matches result presented

round(mean(ANCOVAEstimatorB1Obs)-5,1)
# 0
# Matches result presented

#95%CI
round(mean(ANCOVAEstimatorB1CI),2)
# 0.95
# Matches result presented

round(var(ANCOVAEstimatorB1Obs),3)
# 0.135

round((1/n0 + 1/n1)*
  (sigma^2 + nu^2 + delta1^2 - ((sigma^2)/(1+((delta0^2)/sigma^2)))),3)
# 0.135
# Matches result presented


# Result 29, Result 30 and Result 34
ANCOVAEstimatorCLB2True = c(NULL)
ANCOVAEstimatorCLB2Obs = c(NULL)
ANCOVAEstimatorCLB1True = c(NULL)
ANCOVAEstimatorCLB1Obs = c(NULL)
ANCOVAEstimatorCLB1CI = c(NULL)
ANCOVAVar = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre = rnorm(n0+n1,mu,sigma)
  yPre = YPre + rnorm(n0+n1,0,delta0)
  yPost = YPre +tau*YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANCOVADF = data.frame(YPre = YPre, yPre=yPre,yPost=yPost,Group=c(rep("0",n0),rep("1",n1)))
  ANCOVAEstimatorCLB1True[i]=summary(lm(yPost~YPre+Group,data=ANCOVADF))$coefficients[[3,1]]
  ANCOVAEstimatorCLB1Obs[i]=summary(lm(yPost~yPre+Group,data=ANCOVADF))$coefficients[[3,1]]
  ANCOVAEstimatorCLB2True[i]=summary(lm(yPost~YPre+Group,data=ANCOVADF))$coefficients[[2,1]]
  ANCOVAEstimatorCLB2Obs[i]=summary(lm(yPost~yPre+Group,data=ANCOVADF))$coefficients[[2,1]]
```

```
  ANCOVAVar[i] = (1/n0 + 1/n1 +
                   (((mean(yPre[(n0+1):(n0+n1)])-mean(yPre[1:n0]))^2)/
                      (sum((yPre[(n0+1):(n0+n1)]-mean(yPre[(n0+1):(n0+n1)]))^2)+
                         sum((yPre[1:n0]-mean(yPre[1:n0]))^2))))*
    (((1+tau)^2)*sigma^2 + nu^2 + delta1^2 - ((((1+tau)^2)*sigma^2)/(1+((delta0^2)/sigma^2))))
  ANCOVAEstimatorCLB1CI[i] = ANCOVAEstimatorCLB1Obs[i]-(1.96*sqrt(ANCOVAVar[i]))< Delta1-Delta0 &
    ANCOVAEstimatorCLB1Obs[i]+(1.96*sqrt(ANCOVAVar[i]))>Delta1-Delta0}

# B2 EstimatorCL no measurement error and measurement error
round(mean(ANCOVAEstimatorCLB2True),2)
# 0.7
1+tau
# 0.7
# Matches result presented

round(mean(ANCOVAEstimatorCLB2Obs),2)
# 0.51
round((1+tau)*(sigma^2/(sigma^2+delta0^2)),2)
# 0.51
# Matches result presented

# Bias in B1 Estimator no measurement error and measurement error
round(mean(ANCOVAEstimatorCLB1True)-5,2)
# 0
# Matches result presented

round(mean(ANCOVAEstimatorCLB1Obs)-5,1)
# 0
# Matches result presented

#95%CI
round(mean(ANCOVAEstimatorCLB1CI),2)
# 0.95
# Matches result presented

round(var(ANCOVAEstimatorCLB1Obs),3)
# 0.108

round((1/n0 + 1/n1)*
        (((1+tau)^2)*sigma^2 + nu^2 + delta1^2 - ((((1+tau)^2)*sigma^2)/(1+((delta0^2)/sigma^2)))),3)
# 0.108
# Matches result presented

# Result 31
ANCOVAEstimatorTrueIMB = c(NULL)
ANCOVAEstimatorObsIMB = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre0 = rnorm(n0,mu,sigma)
  YPre1 = YPre0 + delta
  YPre = c(YPre0,YPre1)
  yPre = YPre + rnorm((n0+n1),0,delta0)
  yPost = YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANCOVADF = data.frame(YPre = YPre, yPre=yPre,yPost=yPost,Group=c(rep("0",n0),rep("1",n1)))
  ANCOVAEstimatorTrueIMB[i]=summary(lm(yPost~YPre+Group,data=ANCOVADF))$coefficients[[3,1]]
  ANCOVAEstimatorObsIMB[i]=summary(lm(yPost~yPre+Group,data=ANCOVADF))$coefficients[[3,1]]}

# Bias true values
round(mean(ANCOVAEstimatorTrueIMB)-5,2)
# 0
# Matches result presented

# Bias observed values
round(mean(ANCOVAEstimatorObsIMB)-5,2)
# 1.32
round((1-(sigma^2/(sigma^2+delta0^2)))*5,2)
# 1.32
# Matches result presented
```

```
# Result 32
ANCOVAEstimatorTrueIMBCL = c(NULL)
ANCOVAEstimatorObsIMBCL = c(NULL)
set.seed(123)
for(i in 1:10000){
  YPre0 = rnorm(n0,mu,sigma)
  YPre1 = YPre0 + delta
  YPre = c(YPre0,YPre1)
  yPre = YPre + rnorm((n0+n1),0,delta0)
  yPost = YPre +tau*YPre + c(rep(Delta0,n0),rep(Delta1,n1)) +
    rnorm(n0+n1,0,nu) + rnorm(n0+n1,0,delta1)
  ANCOVADF = data.frame(YPre = YPre, yPre=yPre,yPost=yPost,Group=c(rep("0",n0),rep("1",n1)))
  ANCOVAEstimatorTrueIMBCL[i]=summary(lm(yPost~YPre+Group,data=ANCOVADF))$coefficients[[3,1]]
  ANCOVAEstimatorObsIMBCL[i]=summary(lm(yPost~yPre+Group,data=ANCOVADF))$coefficients[[3,1]]}

# Bias true values
round(mean(ANCOVAEstimatorTrueIMBCL)-5,2)
# 0
# Matches result presented

# Bias observed values
round(mean(ANCOVAEstimatorObsIMBCL)-5,2)
# 0.93
round((1+tau)*(1-(sigma^2/(sigma^2+delta0^2)))*5,2)
# 0.93
# Matches result presented
```

Appendix F: Overview of simulation and additional derivation of important results.

The simulations comprised generation of data sets for nine outcomes comprising three outcomes from three different domains such that the intra-domain correlations (in both baseline and change values) were higher than inter-domain correlations. Different sample size, measurement error, and ATEs were simulated and each subjected to analysis using the post-score, ANOVA interaction, and ANCOVA statistical tests. The major aims of the simulation study were to investigate the effects of different data generating mechanisms and baseline imbalances on statistical inferences made. The different data generating mechanisms comprised a spectrum of no influence of baseline value on change score, to a large influence of baseline value on change score. This effect is also referred to as an intervention differential effect. To compare these effects, the change score variance was kept constant. For the independent case

$Y_{ij1} = Y_{ij0} + \Delta_j + \xi_{ij1}$,

we have the change score variance $\mathrm{Var}(Y_{ij1} - Y_{ij0}) = \nu_1^2$.

For the constrained linear case

$Y_{ij1} = Y_{ij0} + \Delta_j + \tau Y_{ij0} + \xi_{ij1}$,

we have the change score variance $\mathrm{Var}(Y_{ij1} - Y_{ij0}) = \tau^2\sigma_0^2 + \tilde{\nu}_1^2$.

Across all simulations we set $\sigma_0^2 = 1$. To change the influence of baseline value on change score and maintain a constant change variance, we set $\tau = -\sqrt{c}\nu_1$ and $\tilde{\nu}_1^2 = (1-c)\nu_1^2$, where $0 < c \le 1$ is a proportion that was ultimately set to 0.25 for a small effect and 0.5 for a medium effect. With this specification for the constrained linear case we have that

$\mathrm{Var}(Y_{ij1} - Y_{ij0}) = \tau^2\sigma_0^2 + \tilde{\nu}_1^2 = c\nu_1^2 + (1-c)\nu_1^2 = \nu_1^2$.

The influence of intervention differential effect on precision.

For the post score model and using Result 17 we see that for different values of c we have

$$\begin{aligned}\mathrm{Var}(\hat{\beta}_1) &= \frac{(1+\tau)^2\sigma_0^2+\tilde{\nu}_1^2+\delta_1^2}{n_0} + \frac{(1+\tau)^2\sigma_0^2+\tilde{\nu}_1^2+\delta_1^2}{n_1}\\ &= \frac{(1-\sqrt{c}\nu_1)^2\sigma_0^2+(1-c)\nu_1^2+\delta_1^2}{n_0} + \frac{(1-\sqrt{c}\nu_1)^2\sigma_0^2+(1-c)\nu_1^2+\delta_1^2}{n_1}\\ &= \frac{(1-2\sqrt{c}\nu_1+c\nu_1^2)+(1-c)\nu_1^2+\delta_1^2}{n_0} + \frac{(1-2\sqrt{c}\nu_1+c\nu_1^2)+(1-c)\nu_1^2+\delta_1^2}{n_1}\\ &= \frac{1+\nu_1^2-2\sqrt{c}\nu_1+\delta_1^2}{n_0} + \frac{1+\nu_1^2-2\sqrt{c}\nu_1+\delta_1^2}{n_1},\end{aligned}$$

hence we can see that for greater intervention differential effects (higher values of c) under the constraint of constant change score variance (and assuming negative effects of higher baseline values on change score), the precision increases.

In contrast, for the ANOVA interaction model and using Result 24 we have

$$\begin{aligned}\mathrm{Var}(\hat{\beta}_3) &= \frac{(\tau^2\sigma_0^2+\delta_0^2+\tilde{\nu}_1^2+\delta_1^2)}{n_0} + \frac{(\tau^2\sigma_0^2+\delta_0^2+\tilde{\nu}_1^2+\delta_1^2)}{n_1}\\ &= \frac{(c\nu_1^2+\delta_0^2+(1-c)\nu_1^2+\delta_1^2)}{n_0} + \frac{(c\nu_1^2+\delta_0^2+(1-c)\nu_1^2+\delta_1^2)}{n_1}\\ &= \frac{(\delta_0^2+\nu_1^2+\delta_1^2)}{n_0} + \frac{(\delta_0^2+\nu_1^2+\delta_1^2)}{n_1},\end{aligned}$$

which we can see is independent of any intervention differential effect.

For the ANCOVA model and using Result 34 we obtain an expression similar to the post score model

$$\begin{aligned}\mathrm{Var}(\hat{\beta}_1|y_{ij0}) &= \left(\frac{1}{n_0} + \frac{1}{n_1} + \frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}\right)\left((1+\tau)^2\sigma_0^2 + \tilde{\nu}_1^2 + \delta_1^2 - \frac{(1+\tau)^2\sigma_0^2}{\left(1+\frac{\delta_0^2}{\sigma_0^2}\right)}\right)\\ &= \left(\frac{1}{n_0} + \frac{1}{n_1} + \frac{(\bar{y}_{.10}-\bar{y}_{.00})^2}{\sum_{i=1}^{n_0}(y_{i00}-\bar{y}_{.00})^2+\sum_{i=1}^{n_1}(y_{i10}-\bar{y}_{.10})^2}\right)\left(1 + \nu_1^2 - 2\sqrt{c}\nu_1 + \delta_1^2 - \frac{(1+c\nu_1^2-2\sqrt{c}\nu_1)}{(1+\delta_0^2/\sigma_0^2)}\right).\end{aligned}$$

Examining the c terms we have $-2\sqrt{c}\nu_1\left(1-\frac{1}{(1+\delta_0^2/\sigma_0^2)}\right) - \frac{c\nu_1^2}{(1+\delta_0^2/\sigma_0^2)}$, hence we can see that for greater intervention differential effects the precision increases.

Appendix G: R code for simulations

```
library(MASS)
library(reshape2)
library(ggplot2)
library(dplyr)
library(tidyr)
library(nlme)
library(foreach)
library(doParallel)
library(data.table)
library(NLP)
library(corrplot)
library(Hmisc)


######## Functions to create data, check data, and perform analyses ########

##### Create data
# Note that the data we create represents the true scores of participants.
# Measurement error is added in the analysis section.

### Simulate baseline data

# Baseline data is simulated for two groups according to standard normal
# distribution (mean: 0, sd: 1). We refer to the 1st group as the standard
# intervention, and the second group as the test intervention.

# Data are simulated for nine variables representing three different outcomes
# across three domains (Strength/Power/Speed).

# The "scale" of the different variables is introduced when considering the
# improvement from baseline to post-intervention, where strength variables exhibit
# the largest improvements and the greater variance in change scores.

# The collective data are simulated from a multivariate normal distribution with
#  intra- and inter-domain correlations.

# We also simulate the data under two conditions. One is no imbalance, that is,
# the expectation of both groups is the same. The other condition is an imbalance of
# magnitude \delta.This imbalance is created simply, by simulating data for
# the standard intervention,then creating the test intervention that consists
# of the same values but each with \delta added.

# The arguments for the function are the number of individuals in each group N,
# the intra- and inter-domain correlations, and the imbalance magnatidue \delta.

BaselineFun = function(N,IntraCor,InterCor,Imbalance){
  # Sample from a multivariate normal distribution for 2 groups, each of size N,
  # mean of 0, sd = 1, and covariance matrix with intra and inter correlations set.
  Base = mvrnorm(2*N, rep(0,9),
               matrix(c(c(1,rep(IntraCor,2),rep(InterCor,6)),
                    c(IntraCor,1,IntraCor,rep(InterCor,6)),
                    c(rep(IntraCor,2),1,rep(InterCor,6)),

                    c(rep(InterCor,3),1,rep(IntraCor,2),rep(InterCor,3)),
                    c(rep(InterCor,3),IntraCor,1,IntraCor,rep(InterCor,3)),
                    c(rep(InterCor,3),rep(IntraCor,2),1,rep(InterCor,3)),

                    c(rep(InterCor,6),1,rep(IntraCor,2)),
                    c(rep(InterCor,6),IntraCor,1,IntraCor),
                    c(rep(InterCor,6),rep(IntraCor,2),1)),ncol=9))

  # If baseline imbalance is set to 0 then we use the matrix above
  if(Imbalance==0){
    Baseline = Base}

  # If baseline imbalance is not 0 then we use the data from the standard intervention and
  # create the test intervention with the imbalance added to all values.
```

```
  if(Imbalance!=0){
    Baseline = rbind(Base[1:N,],(Base[1:N,]+ matrix(Imbalance,nrow=N,ncol=9)))}

  return(Baseline)}

### Simulate post-intervention data

# We write a function that creates change data from a multivariate normal distribution.
# We start with the covariance matrix of the change. We assume that the covariance is the
# same across the groups (that is we only consider the homogenous case).

# Within the homogenous case, there are two data generating mechanisms that we
# wish to consider. The first is the independence case, this is where the change
# score from an individual is not related to the baseline value and the variance of the
# change score is equal to \nu(^2)_1.This can then be added to the baseline scores so that
# the variance of the post-intervention scores is equal to \sigma(^2)_0 + \nu(^2)_1.

# We also set our covariance matrix for the change scores such that that there are
# intra- and inter-domain correlations.

# The arguments for the function are the standard deviation of the change scores for
# the different domains, and the intra- and inter-domain correlation change scores.

ChangeCovMFun = function(StrengthSD,PowerSD,SprintSD){
  # The standard deviation of the chance scores is the same for both groups and differs across outcome domains
  ChangeCovM =  matrix(c(c(StrengthSD^2,rep(IntraChangeCor*StrengthSD*StrengthSD,2),
                         rep(InterChangeCor*StrengthSD*PowerSD,3),rep(InterChangeCor*StrengthSD*SprintSD,3)),
                       c(IntraChangeCor*StrengthSD*StrengthSD,StrengthSD^2,IntraChangeCor*StrengthSD*StrengthSD,
                         rep(InterChangeCor*StrengthSD*PowerSD,3),rep(InterChangeCor*StrengthSD*SprintSD,3)),
                       c(rep(IntraChangeCor*StrengthSD*StrengthSD,2),StrengthSD^2,
                         rep(InterChangeCor*StrengthSD*PowerSD,3),rep(InterChangeCor*StrengthSD*SprintSD,3)),

                       c(rep(InterChangeCor*StrengthSD*PowerSD,3),PowerSD^2,rep(IntraChangeCor*PowerSD*PowerSD,2),
                         rep(InterChangeCor*PowerSD*SprintSD,3)),
                       c(rep(InterChangeCor*StrengthSD*PowerSD,3),IntraChangeCor*PowerSD*PowerSD,PowerSD^2,IntraChangeCor*PowerSD*PowerS
        D,
                         rep(InterChangeCor*PowerSD*SprintSD,3)),
                       c(rep(InterChangeCor*StrengthSD*PowerSD,3),rep(IntraChangeCor*PowerSD*PowerSD,2),PowerSD^2,
                         rep(InterChangeCor*PowerSD*SprintSD,3)),

                       c(rep(InterChangeCor*StrengthSD*SprintSD,3),rep(InterChangeCor*PowerSD*SprintSD,3),
                         SprintSD^2,rep(IntraChangeCor*SprintSD*SprintSD,2)),
                       c(rep(InterChangeCor*StrengthSD*SprintSD,3),rep(InterChangeCor*PowerSD*SprintSD,3),
                         IntraChangeCor*SprintSD*SprintSD,SprintSD^2,IntraChangeCor*SprintSD*SprintSD),
                       c(rep(InterChangeCor*StrengthSD*SprintSD,3),rep(InterChangeCor*PowerSD*SprintSD,3),
                         rep(IntraChangeCor*SprintSD*SprintSD,2),SprintSD^2)),ncol=9)
  return(ChangeCovM)}

# We now consider the constrained linear case where the change score from an individual
# is related to the baseline value. The variance of the post scores are the same for both groups
# and equal to (1+\tau)^2*\sigma(^2)_0 + \nu(^2)_1. The variance of the change is equal to
# \tau^2*\sigma(^2)_0 + \nu(^2)_1.We also ensure that the variance of the change in the constrained linear
# case is equal to the variance of the independence case.

# We investigate two different cases, where the \tau coefficient causes a change that accounts for
# 25 and 50% of the change variation. Using proportions we set c to 0.25 or 0.5. We achieve this by setting
# \tau^2*\sigma(^2)_0 equal to c*\nu(^2)_1 used in the independence case and then
# include an additional variation term that is equal to (1-c)*\nu(^2)_1
TauMatrixFun = function(N,StrengthSD,PowerSD,SprintSD,proportion){
  StrengthTau = -sqrt(StrengthSD^2 - proportion*(StrengthSD^2))
  PowerTau = -sqrt(PowerSD^2 - proportion*(PowerSD^2))
  SprintTau = -sqrt(SprintSD^2 - proportion*(SprintSD^2))
  StrengthMatrix = matrix(StrengthTau,nrow=2*N, ncol=3)
  PowerMatrix = matrix(PowerTau,nrow=2*N, ncol=3)
  SprintMatrix = matrix(SprintTau,nrow=2*N, ncol=3)
  MatrixOut = cbind(StrengthMatrix,PowerMatrix,SprintMatrix)
  return(MatrixOut)}

# Now we create a function that outputs our baseline and post-intervention data.
```

```
# The post intervention data uses the \tau coefficient on the baseline values and then
# adds the remaining variance terms and intra- and inter-domain change correlations.

# As the mean of the baseline values is 0,overall, the \tau coefficient doesnt change the mean.
# Instead we map the mean change of the standard intervention to the small/medium/large effect size
# based on the domain.Individuals in the test intervention then experience a mean change relative
# to the standard group that is equal to zero or small/medium/large positive comparative effect
# which is the same for all domains.

# The arguments to the function are, the number of iterations (data sets) that we want,
# the standard deviation of the change scores for the different domains, the change for the
# standard intervention for the different domains, the additional comparative change
# for the test intervention, the proportion for which the covariance matrix accounts for the
# change variance, and if there is any imblance in the baseline data.


PrePostFun = function(Iter,StrengthSD,PowerSD,SprintSD,
                    StrengthChange, PowerChange, SprintChange,
                    Comparative, proportion,Imbalance){
  PreA = array(NA,c(2*N,9,Iter))
  PostA = array(NA,c(2*N,9,Iter))
  ChangeCovM = proportion*(ChangeCovMFun(StrengthSD,PowerSD,SprintSD))
  TauMatrix = TauMatrixFun(N,StrengthSD,PowerSD,SprintSD,proportion)
  for(i in 1:Iter){
    PreA[,,i] = BaselineFun(N,IntraCor,InterCor,Imbalance)

    ChangeM = rbind(mvrnorm(N, c(rep(StrengthChange,3),rep(PowerChange,3),rep(SprintChange,3)),
                ChangeCovM),
            mvrnorm(N, c(rep(StrengthChange+Comparative,3),rep(PowerChange+Comparative,3),rep(SprintChange+Comparative,3)),
                ChangeCovM))

    PostA[,,i]=PreA[,,i] + (PreA[,,i]*TauMatrix) + ChangeM}
  Output = list(round(PreA,3),round(PostA,3))
  names(Output) = c("Pre","Post")
  return(Output)}

####### Checks on data


# Function to calculate the mean across the three different domains
Fun3 = function(x){
  c(mean(x[1:3]),mean(x[4:6]),mean(x[7:9]))
}

CheckDataFunShort = function(Baseline,PostData){
  ChangeData = array(NA,c(2*N,9,Iter))
  for(i in 1:Iter){
    ChangeData[,,i]=PostData[,,i]-Baseline[,,i]
  }
  MeansBaselineStandard = round(Fun3(apply(apply(Baseline[1:N,,], c(1,2), mean),2,mean)),2)
  MeansPostStandard = round(Fun3(apply(apply(PostData[1:N,,], c(1,2), mean),2,mean)),2)
  MeansChangeStandard = round(Fun3(apply(apply(ChangeData[1:N,,], c(1,2), mean),2,mean)),2)
  SDBaselineStandard = round(Fun3(apply(apply(Baseline[1:N,,], c(1,2), sd),2,mean)),2)
  SDPostStandard = round(Fun3(apply(apply(PostData[1:N,,], c(1,2), sd),2,mean)),2)
  SDChangeStandard = round(Fun3(apply(apply(ChangeData[1:N,,], c(1,2), sd),2,mean)),2)

  MeansBaselineTest = round(Fun3(apply(apply(Baseline[(N+1):(2*N),,], c(1,2), mean),2,mean)),2)
  MeansPostTest = round(Fun3(apply(apply(PostData[(N+1):(2*N),,], c(1,2), mean),2,mean)),2)
  MeansChangeTest = round(Fun3(apply(apply(ChangeData[(N+1):(2*N),,], c(1,2), mean),2,mean)),2)
  SDBaselineTest = round(Fun3(apply(apply(Baseline[(N+1):(2*N),,], c(1,2), sd),2,mean)),2)
  SDPostTest = round(Fun3(apply(apply(PostData[(N+1):(2*N),,], c(1,2), sd),2,mean)),2)
  SDChangeTest = round(Fun3(apply(apply(ChangeData[(N+1):(2*N),,], c(1,2), sd),2,mean)),2)


  Out = list(MeansBaselineStandard,MeansBaselineTest,
          MeansPostStandard,MeansPostTest,
          MeansChangeStandard,MeansChangeTest,

          SDBaselineStandard,SDBaselineTest,
          SDPostStandard,SDPostTest,
```

```
            SDChangeStandard,SDChangeTest)

  names(Out)=c("MeansBaselineStandard","MeansBaselineTest",
             "MeansPostStandard","MeansPostTest",
             "MeansChangeStandard","MeansChangeTest",

             "SDBaselineStandard","SDBaselineTest",
             "SDPostStandard","SDPostTest",
             "SDChangeStandard","SDChangeTest")
  return(Out)}

# Combine the abridged data check into a table for export
# We combine data from 12 different data "experiments".

TableFun = function(x1,x2,x3,x4,x5,x6,x7,x8,x9){
  TableNames = c("Simulation","Means_Pre_Standard","Means_Pre_Test",
              "Means_Post_Standard","Means_Post_Test",
              "Means_Change_Standard","Means_Change_Test",
              "SD_Pre_Standard","SD_Pre_Test",
              "SD_Post_Standard","SD_Post_Test",
              "SD_Change_Standard","SD_Change_Test")
  T0 = data.table(TableNames)
  T1 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x1))),3))),data.table(do.call(rbind, x1))))
  T2 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x2))),3))),data.table(do.call(rbind, x2))))
  T3 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x3))),3))),data.table(do.call(rbind, x3))))
  T4 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x4))),3))),data.table(do.call(rbind, x4))))
  T5 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x5))),3))),data.table(do.call(rbind, x5))))
  T6 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x6))),3))),data.table(do.call(rbind, x6))))
  T7 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x7))),3))),data.table(do.call(rbind, x7))))
  T8 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x8))),3))),data.table(do.call(rbind, x8))))
  T9 =rbindlist(list(data.table(t(rep(gsub('.{2}$', '', as.String(enexpr(x9))),3))),data.table(do.call(rbind, x9))))
  T1C =data.table(T0,T1,T2,T3)
  T2C =data.table(T0,T4,T5,T6)
  T3C =data.table(T0,T7,T8,T9)
  Out = rbind(T1C,T2C,T3C)
  colnames(Out)=c("Variables",rep(c("Strength","Power","Speed"),3))
  return(Out)}

####### Analysis of the data
# We now perform analysis on the data.For each variable we run a t-test on the post scores,
# an ANCOVA and a repeated measures ANOVA. For each test we record the group effect estimate,
# the standard error, the statistic value, and the p value.

# We create a list of variable names (one for the 9 variables baseline and one for the 9 variables
# post-intervention) that can be used in our loop.
DVL= c("X1","X2","X3","X4","X5","X6","X7","X8","X9","X10","X11","X12","X13","X14","X15",
       "X16","X17","X18")

# For our function we have to run the analysis on different measurement error values and
# for different sample sizes.

# The arguments for the function are the baseline and post-intervention arrays, and the
# error sd, such that we will run this function for no error, small, medium and large error.

# For each data set we create a separate analysis array for each test,
# that saves for each variable (15 in total),the four different results
# (estimate, SE, statistic, p-value) for the four different sample sizes.
# Hence each analysis array has 15 rows, 16 columns and a third dimension equal to the
# number of iterations.

AnalysisFun = function(Baseline,PostData,ErrorSd){
  # Collect results
  TResult=array(NA, c(9,16,Iter))
  ANCOVAResult=array(NA, c(9,16,Iter))
  ANOVAglsResult=array(NA, c(9,16,Iter))
  # We create two different data frames, one long format for the t-test and ANOVA,
  # one wide for the ANCOVA. For each we add measurement error to baseine and post-intervention data
  for(i in 1:Iter){
    DataA = rbind((Baseline[,,i]+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)),
              (PostData[,,i]+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)))
```

```
    DataB = cbind((Baseline[,,i]+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)),
                (PostData[,,i]+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)))
    # Create data frames to perform analyses
    DataADF = data.frame(DataA)
    DataBDF = data.frame(DataB)
    DataADF$ID = rep(1:(2*N),2)
    DataADF$Time = c(rep("Baseline",(2*N)),rep("Post",(2*N)))
    DataADF$Group = rep(c(rep("Standard",N),rep("Test",N)),2)
    DataBDF$Group = c(rep("Standard",N),rep("Test",N))

    # For each set of analyses we run the analysis on the four different sample sizes: N, N0, N1, N2
    for (j in 1:9) {
     Y1 = DVL[j]
     Y2 = DVL[j+9]
     # T-test
     TResult[j,1:4,i] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data =
        DataADF[c(((2*N)+1):((2*N)+N0),((3*N)+1):((3*N)+N0)),]))$coefficients[2,])
     TResult[j,5:8,i] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data =
        DataADF[c(((2*N)+1):((2*N)+N1),((3*N)+1):((3*N)+N1)),]))$coefficients[2,])
     TResult[j,9:12,i] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data =
        DataADF[c(((2*N)+1):((2*N)+N2),((3*N)+1):((3*N)+N2)),]))$coefficients[2,])
     TResult[j,13:16,i] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data = DataADF[((2*N)+1):(4*N),]))$coefficients[2,])

     # Ancova
     ANCOVAResult[j,1:4,i] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data =
        DataBDF[c(1:N0,(N+1):(N+N0)),]))$coefficients[3,])
     ANCOVAResult[j,5:8,i] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data =
        DataBDF[c(1:N1,(N+1):(N+N1)),]))$coefficients[3,])
     ANCOVAResult[j,9:12,i] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data =
        DataBDF[c(1:N2,(N+1):(N+N2)),]))$coefficients[3,])
     ANCOVAResult[j,13:16,i] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data = DataBDF))$coefficients[3,])

     # Repeated measures ANOVA with sphericity
     ANOVAglsResult[j,1:4,i] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                  data=DataADF[c(1:N0,(N+1):(N+N0),((2*N)+1):((2*N)+N0),((3*N)+1):((3*N)+N0)),]))$tTable[4,])
     ANOVAglsResult[j,5:8,i] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                  data=DataADF[c(1:N1,(N+1):(N+N1),((2*N)+1):((2*N)+N1),((3*N)+1):((3*N)+N1)),]))$tTable[4,])
     ANOVAglsResult[j,9:12,i] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                  data=DataADF[c(1:N2,(N+1):(N+N2),((2*N)+1):((2*N)+N2),((3*N)+1):((3*N)+N2)),]))$tTable[4,])
     ANOVAglsResult[j,13:16,i] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                  data=DataADF))$tTable[4,])

    }
   }

  OutF = list(TResult,ANCOVAResult,ANOVAglsResult)
  names(OutF)=c("T-test","ANCOVA","ANOVAgls")
  return(OutF)}

# For a large number of iterations (e.g. 1000+), the above function is likely to be too slow.
# Therefore we also include a parallelised version of the function.

AnalysisPFun = function(Baseline,PostData,ErrorSd){
  TResult=array(NA, c(9,16))
  ANCOVAResult=array(NA, c(9,16))
  ANOVAglsResult=array(NA, c(9,16))
  DataA = rbind((Baseline+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)),
              (PostData+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)))
  DataB = cbind((Baseline+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)),
              (PostData+matrix(rnorm(2*N*9,0,ErrorSd),nrow=2*N,ncol=9,byrow = TRUE)))
  DataADF = data.frame(DataA)
  DataBDF = data.frame(DataB)
  DataADF$ID = rep(1:(2*N),2)
  DataADF$Time = c(rep("Baseline",(2*N)),rep("Post",(2*N)))
  DataADF$Group = rep(c(rep("Standard",N),rep("Test",N)),2)
  DataBDF$Group = c(rep("Standard",N),rep("Test",N))

  for (j in 1:9) {
    Y1 = DVL[j]
    Y2 = DVL[j+9]
```

```
    TResult[j,1:4] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data =
        DataADF[c(((2*N)+1):((2*N)+N0),((3*N)+1):((3*N)+N0)),]))$coefficients[2,])
    TResult[j,5:8] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data =
        DataADF[c(((2*N)+1):((2*N)+N1),((3*N)+1):((3*N)+N1)),]))$coefficients[2,])
    TResult[j,9:12] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data =
        DataADF[c(((2*N)+1):((2*N)+N2),((3*N)+1):((3*N)+N2)),]))$coefficients[2,])
    TResult[j,13:16] = as.numeric(summary(lm(as.formula(paste(Y1, "~ Group")), data = DataADF[((2*N)+1):(4*N),]))$coefficients[2,])

    ANCOVAResult[j,1:4] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data =
        DataBDF[c(1:N0,(N+1):(N+N0)),]))$coefficients[3,])
    ANCOVAResult[j,5:8] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data =
        DataBDF[c(1:N1,(N+1):(N+N1)),]))$coefficients[3,])
    ANCOVAResult[j,9:12] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data =
        DataBDF[c(1:N2,(N+1):(N+N2)),]))$coefficients[3,])
    ANCOVAResult[j,13:16] = as.numeric(summary(lm(as.formula(paste(Y2, "~",Y1,"+Group")), data = DataBDF))$coefficients[3,])

    ANOVAglsResult[j,1:4] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                 data=DataADF[c(1:N0,(N+1):(N+N0),((2*N)+1):((2*N)+N0),((3*N)+1):((3*N)+N0)),]))$tTable[4,])
    ANOVAglsResult[j,5:8] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                 data=DataADF[c(1:N1,(N+1):(N+N1),((2*N)+1):((2*N)+N1),((3*N)+1):((3*N)+N1)),]))$tTable[4,])
    ANOVAglsResult[j,9:12] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                 data=DataADF[c(1:N2,(N+1):(N+N2),((2*N)+1):((2*N)+N2),((3*N)+1):((3*N)+N2)),]))$tTable[4,])
    ANOVAglsResult[j,13:16] = as.numeric(summary(gls(as.formula(paste(Y1, "~Time*Group")), correlation=corCompSymm(form=~1|ID),
                                 data=DataADF))$tTable[4,])

  }

  OutF = list(TResult,ANCOVAResult,ANOVAglsResult)
  names(OutF)=c("T-test","ANCOVA","ANOVAgls")
  return(OutF)}


# Now that we have our analysis function, we want to package the results together from
# the four different error values.

# Using the parallelised function, at present our results are stored in a list (#Iterations)
# and in each of these a list of 3 (T-test, ANCOVA, ANOVA)
# For each test, we have a matrix with 9 rows and 16 cols, the cols being 4 sets of 4 results
# for the different sample sizes.

# We collapse this into something easy to analyse by saving as a transposed matrix. This gives us
# 9 columns (1 for each variable) and 3*16*Iter rows. We then column bind the four different
# error outputs, so we have 36 columns.

# We turn this into one large data frame. We write this to a CSV file. When we then upload the CSV file
# for analysis.

##### Functions to analyse the data
############################ Analysis ######################################

# Functions

# We now read in our saved data. it adds a first column which we remove.

# We add new column descriptors to analyse our results in blocks of 16
# First we note that the sample sizes,then the statistic type, then the test type.

# We then turn the dataframe into a long format. This puts all variable in order
# 1, then 2, then 3, up to 9. The sequence then repeats for the four different error values

# Function to turn the saved data from AnalysisPFun into a data frame easy to analyse
OutputPDFFun = function(TransposedDataFrame){
  TDF = TransposedDataFrame[,-1]
  # 4 values for the 4 sample sizes, this is then repeated for the 3 tests, for the iterations
  TDF$SampleSize = rep(c(rep("N0",4),rep("N1",4),rep("N2",4),rep("N",4)),3*Iter)
  # Each value repeated for the the 4 sample sizes, this is then repeated for the 3 tests, for the iterations
  TDF$Statistic = rep(c("Estimate", "SE","Stat","Pvalue"),4*3*Iter)
  # 16 values for each test, which is then repeated for the number of iterations
  TDF$Test = rep(c(rep("T-Test",16),rep("ANCOVA",16),rep("ANOVA",16)),Iter)
  LTDF = reshape2::melt(TDF, id.vars=c("Test", "Statistic","SampleSize"))
```

```
  # We have each outcome repeated for the 16 values, for the 3 tests, for the 3 outcomes, for the iterations
  # then repeated for the 4 errors
  LTDF$Outcome = rep(c(rep("Strength",16*3*3*Iter),rep("Power",16*3*3*Iter),
                    rep("Sprint",16*3*3*Iter)),4)
  # One error after the other.
  LTDF$Error = c(rep("Zero",16*3*3*3*Iter),rep("Small",16*3*3*3*Iter),
               rep("Medium",16*3*3*3*Iter),rep("Large",16*3*3*3*Iter))
  return(LTDF)}


# Output with filter and group
OutputGeneral = function(Data, Groupargs,...){

  byG = syms(Groupargs)

  Data %>%
    filter(...) %>%
    group_by(!!!byG) %>%
    summarise(mean = round(mean(value),3),sd = round(sd(value),3),
            Q25 = round(quantile(value, 0.25),3),Median = round(median(value),3),
            Q75 = round(quantile(value, 0.75),3))
}

# Depending on filtering (e.g. to Statistic=="Pvalue") and grouping calculates
# the proportion of p values less than 0.05

# Pvalue 1
Pvalue1 = function(Data, Groupargs,...){
  byG = syms(Groupargs)
  Data %>%
    filter(...) %>%
    group_by(!!!byG) %>%
    summarise(P005 = round(100*(mean(value<0.05)),1))
}

OutputPvalue3DFFun = function(TransposedDataFrame,minormax){
  TDF = TransposedDataFrame[,-1]
  # 4 values for the 4 sample sizes, this is then repeated for the 3 tests, for the iterations
  TDF$SampleSize = rep(c(rep("N0",4),rep("N1",4),rep("N2",4),rep("N",4)),3*Iter)
  # Each value repeated for the the 4 sample sizes, this is then repeated for the 3 tests, for the iterations
  TDF$Statistic = rep(c("Estimate", "SE","Stat","Pvalue"),4*3*Iter)
  # 16 values for each test, which is then repeated for the number of iterations
  TDF$Test = rep(c(rep("T-Test",16),rep("ANCOVA",16),rep("ANOVA",16)),Iter)
  TDF = TDF[TDF$Statistic=="Pvalue",]
  OutDF = TDF[c(37:39)]
  OutDF$StrengthError0 = apply(TDF[,1:3],1,minormax)
  OutDF$PowerError0 = apply(TDF[,4:6],1,minormax)
  OutDF$SprintError0 = apply(TDF[,7:9],1,minormax)
  OutDF$StrengthErrorS = apply(TDF[,10:12],1,minormax)
  OutDF$PowerErrorS = apply(TDF[,13:15],1,minormax)
  OutDF$SprintErrorS = apply(TDF[,16:18],1,minormax)
  OutDF$StrengthErrorM = apply(TDF[,19:21],1,minormax)
  OutDF$PowerErrorM = apply(TDF[,22:24],1,minormax)
  OutDF$SprintErrorM = apply(TDF[,25:27],1,minormax)
  OutDF$StrengthErrorL = apply(TDF[,28:30],1,minormax)
  OutDF$PowerErrorL = apply(TDF[,31:33],1,minormax)
  OutDF$SprintErrorL = apply(TDF[,34:36],1,minormax)
  LTDF = reshape2::melt(OutDF, id.vars=c("Test", "Statistic","SampleSize"))
  # We have each outcome repeated for the 4 values, for the 3 tests,for the iterations
  # then repeated for the 4 errors
  LTDF$Outcome = rep(c(rep("Strength",4*3*Iter),rep("Power",4*3*Iter),
                    rep("Sprint",4*3*Iter)),4)
  # One error after the other.
  LTDF$Error = c(rep("Zero",4*3*3*Iter),rep("Small",4*3*3*Iter),
               rep("Medium",4*3*3*Iter),rep("Large",4*3*3*Iter))
  return(LTDF)}

OutputPvalue9DFFun = function(TransposedDataFrame,minormax){
  TDF = TransposedDataFrame[,-1]
  # 4 values for the 4 sample sizes, this is then repeated for the 3 tests, for the iterations
```

```
 TDF$SampleSize = rep(c(rep("N0",4),rep("N1",4),rep("N2",4),rep("N",4)),3*Iter)
 # Each value repeated for the the 4 sample sizes, this is then repeated for the 3 tests, for the iterations
 TDF$Statistic = rep(c("Estimate", "SE","Stat","Pvalue"),4*3*Iter)
 # 16 values for each test, which is then repeated for the number of iterations
 TDF$Test = rep(c(rep("T-Test",16),rep("ANCOVA",16),rep("ANOVA",16)),Iter)
 TDF = TDF[TDF$Statistic=="Pvalue",]
 OutDF = TDF[c(37:39)]
 OutDF$SPSError0 = apply(TDF[,1:9],1,minormax)
 OutDF$SPSErrorS = apply(TDF[,10:18],1,minormax)
 OutDF$SPSErrorM = apply(TDF[,19:27],1,minormax)
 OutDF$SPSErrorL = apply(TDF[,28:36],1,minormax)
 LTDF = reshape2::melt(OutDF, id.vars=c("Test", "Statistic","SampleSize"))

 # One error after the other.
 LTDF$Error = c(rep("Zero",4*3*Iter),rep("Small",4*3*Iter),
             rep("Medium",4*3*Iter),rep("Large",4*3*Iter))
 return(LTDF)}


######################  Creation and analysis of data  ######################################
# Model parameters

# Sample sizes and iterations
Iter = 10000
N0 = 10
N1 = 15
N2 = 25
N = 50

IntraCor = 0.9
InterCor = 0.7

IntraChangeCor = 0.7
InterChangeCor = 0.5

# SDs
StSD = 1.25*0.6
PSD = 1.25*0.5
SpSD = 1.25*0.4
# Construct Effect size S/M/L
StSES = 0.25
PSES = 0.2
SpSES = 0.05

StMES = 0.6
PMES = 0.5
SpMES = 0.4

StLES = 1
PLES = 0.8
SpLES = 0.7

# Comparative Effect size 0/S/M/L
C0ES = 0
CSES = 0.15
CMES = 0.3
CLES = 0.5

# IDE Zero/25%/50%/ 1-c values
IDE0 = 1
IDES = 0.75
IDEM = 0.5


# Imbalance Zero +-/S/M/L
IMB0 = 0
IMBNS = -0.5
IMBPS = 0.5

# Error values added to data S/M/L
```

```
ESdS = 0.1
ESdM = 0.25
ESdL = 0.5

# Data structure:
# 1) S/M/L Improvements
# 2) 0/S/M/L Comparative
# 3) 0/25%/50% IDE of baseline referret to as 0/S/M
# 4) 0/+S,-S/ baseline Imbalance


n.cores = parallel::detectCores() - 2
my.cluster = parallel::makeCluster(
  n.cores,
  type = "PSOCK"
)
doParallel::registerDoParallel(cl = my.cluster)
# parallel::stopCluster(cl = my.cluster)

######## Analysis with zero comparative effect ##############

## Example ofsimulation rum on one full condition
set.seed(123)
IS_C0ES_IDE0_IMB0D = PrePostFun(Iter,StSD,PSD,SpSD,StSES, PSES, SpSES,C0ES, IDE0,IMB0)
IS_C0ES_IDE0_IMB0DC = CheckDataFunShort(IS_C0ES_IDE0_IMB0D$Pre,IS_C0ES_IDE0_IMB0D$Post)
IS_C0ES_IDE0_IMB0_Er0=foreach(i = 1:Iter,.packages='nlme') %dopar%
  AnalysisPFun(Baseline=IS_C0ES_IDE0_IMB0D$Pre[,,i],PostData=IS_C0ES_IDE0_IMB0D$Post[,,i],ErrorSd=0)
IS_C0ES_IDE0_IMB0_ErS=foreach(i = 1:Iter,.packages='nlme') %dopar%
  AnalysisPFun(Baseline=IS_C0ES_IDE0_IMB0D$Pre[,,i],PostData=IS_C0ES_IDE0_IMB0D$Post[,,i],ErrorSd=ESdS)
IS_C0ES_IDE0_IMB0_ErM=foreach(i = 1:Iter,.packages='nlme') %dopar%
  AnalysisPFun(Baseline=IS_C0ES_IDE0_IMB0D$Pre[,,i],PostData=IS_C0ES_IDE0_IMB0D$Post[,,i],ErrorSd=ESdM)
IS_C0ES_IDE0_IMB0_ErL=foreach(i = 1:Iter,.packages='nlme') %dopar%
  AnalysisPFun(Baseline=IS_C0ES_IDE0_IMB0D$Pre[,,i],PostData=IS_C0ES_IDE0_IMB0D$Post[,,i],ErrorSd=ESdL)
write.csv(cbind(t(as.data.frame(IS_C0ES_IDE0_IMB0_Er0)),t(as.data.frame(IS_C0ES_IDE0_IMB0_ErS)),
        t(as.data.frame(IS_C0ES_IDE0_IMB0_ErM)),t(as.data.frame(IS_C0ES_IDE0_IMB0_ErL))),"IS_C0ES_IDE0_IMB0.csv")
```

Appendix H: Result outputs from simulations

Results are presented below for the percentage of tests identified as significant ($p<0.05$) across the different scenarios.

Zero ATE and Zero Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	4.9
ANCOVA	10	Zero	Small	Power	5
ANCOVA	10	Zero	Small	Sprint	4.8
ANCOVA	10	Zero	Medium	Strength	5
ANCOVA	10	Zero	Medium	Power	5.1
ANCOVA	10	Zero	Medium	Sprint	4.8
ANCOVA	10	Zero	Large	Strength	4.9
ANCOVA	10	Zero	Large	Power	4.9
ANCOVA	10	Zero	Large	Sprint	5
ANCOVA	10	Small	Small	Strength	4.8
ANCOVA	10	Small	Small	Power	5.2
ANCOVA	10	Small	Small	Sprint	4.8
ANCOVA	10	Small	Medium	Strength	4.8
ANCOVA	10	Small	Medium	Power	5
ANCOVA	10	Small	Medium	Sprint	4.8
ANCOVA	10	Small	Large	Strength	5.1
ANCOVA	10	Small	Large	Power	5.2
ANCOVA	10	Small	Large	Sprint	4.9
ANCOVA	10	Medium	Small	Strength	4.8
ANCOVA	10	Medium	Small	Power	5.1
ANCOVA	10	Medium	Small	Sprint	4.9
ANCOVA	10	Medium	Medium	Strength	4.9
ANCOVA	10	Medium	Medium	Power	5.1
ANCOVA	10	Medium	Medium	Sprint	5
ANCOVA	10	Medium	Large	Strength	4.9
ANCOVA	10	Medium	Large	Power	5
ANCOVA	10	Medium	Large	Sprint	4.9
ANCOVA	15	Zero	Small	Strength	4.7
ANCOVA	15	Zero	Small	Power	5
ANCOVA	15	Zero	Small	Sprint	4.5
ANCOVA	15	Zero	Medium	Strength	4.8
ANCOVA	15	Zero	Medium	Power	4.9
ANCOVA	15	Zero	Medium	Sprint	4.5
ANCOVA	15	Zero	Large	Strength	4.8
ANCOVA	15	Zero	Large	Power	5
ANCOVA	15	Zero	Large	Sprint	4.9
ANCOVA	15	Small	Small	Strength	4.8
ANCOVA	15	Small	Small	Power	5
ANCOVA	15	Small	Small	Sprint	4.5
ANCOVA	15	Small	Medium	Strength	4.7
ANCOVA	15	Small	Medium	Power	5
ANCOVA	15	Small	Medium	Sprint	4.7
ANCOVA	15	Small	Large	Strength	4.9
ANCOVA	15	Small	Large	Power	5.1

ANCOVA	15	Small	Large	Sprint	4.8
ANCOVA	15	Medium	Small	Strength	4.6
ANCOVA	15	Medium	Small	Power	5
ANCOVA	15	Medium	Small	Sprint	4.6
ANCOVA	15	Medium	Medium	Strength	4.7
ANCOVA	15	Medium	Medium	Power	5.1
ANCOVA	15	Medium	Medium	Sprint	4.9
ANCOVA	15	Medium	Large	Strength	4.9
ANCOVA	15	Medium	Large	Power	4.9
ANCOVA	15	Medium	Large	Sprint	4.8
ANCOVA	25	Zero	Small	Strength	4.8
ANCOVA	25	Zero	Small	Power	5.2
ANCOVA	25	Zero	Small	Sprint	4.9
ANCOVA	25	Zero	Medium	Strength	4.9
ANCOVA	25	Zero	Medium	Power	4.9
ANCOVA	25	Zero	Medium	Sprint	5
ANCOVA	25	Zero	Large	Strength	5
ANCOVA	25	Zero	Large	Power	5.1
ANCOVA	25	Zero	Large	Sprint	5
ANCOVA	25	Small	Small	Strength	4.9
ANCOVA	25	Small	Small	Power	5
ANCOVA	25	Small	Small	Sprint	4.9
ANCOVA	25	Small	Medium	Strength	4.8
ANCOVA	25	Small	Medium	Power	5.1
ANCOVA	25	Small	Medium	Sprint	4.9
ANCOVA	25	Small	Large	Strength	5.1
ANCOVA	25	Small	Large	Power	5
ANCOVA	25	Small	Large	Sprint	4.8
ANCOVA	25	Medium	Small	Strength	4.8
ANCOVA	25	Medium	Small	Power	4.9
ANCOVA	25	Medium	Small	Sprint	5
ANCOVA	25	Medium	Medium	Strength	4.9
ANCOVA	25	Medium	Medium	Power	5
ANCOVA	25	Medium	Medium	Sprint	5
ANCOVA	25	Medium	Large	Strength	4.9
ANCOVA	25	Medium	Large	Power	5.1
ANCOVA	25	Medium	Large	Sprint	4.9
ANCOVA	50	Zero	Small	Strength	5
ANCOVA	50	Zero	Small	Power	5.2
ANCOVA	50	Zero	Small	Sprint	4.9
ANCOVA	50	Zero	Medium	Strength	5
ANCOVA	50	Zero	Medium	Power	5
ANCOVA	50	Zero	Medium	Sprint	4.9
ANCOVA	50	Zero	Large	Strength	5.1
ANCOVA	50	Zero	Large	Power	5.2
ANCOVA	50	Zero	Large	Sprint	5.1
ANCOVA	50	Small	Small	Strength	5
ANCOVA	50	Small	Small	Power	5.2
ANCOVA	50	Small	Small	Sprint	4.9
ANCOVA	50	Small	Medium	Strength	5.1

ANCOVA	50	Small	Medium	Power	5.1
ANCOVA	50	Small	Medium	Sprint	4.8
ANCOVA	50	Small	Large	Strength	5.1
ANCOVA	50	Small	Large	Power	5.1
ANCOVA	50	Small	Large	Sprint	5.1
ANCOVA	50	Medium	Small	Strength	4.9
ANCOVA	50	Medium	Small	Power	5.2
ANCOVA	50	Medium	Small	Sprint	5
ANCOVA	50	Medium	Medium	Strength	5
ANCOVA	50	Medium	Medium	Power	5.2
ANCOVA	50	Medium	Medium	Sprint	5
ANCOVA	50	Medium	Large	Strength	5
ANCOVA	50	Medium	Large	Power	5
ANCOVA	50	Medium	Large	Sprint	4.9
ANOVA	10	Zero	Small	Strength	5.6
ANOVA	10	Zero	Small	Power	5.9
ANOVA	10	Zero	Small	Sprint	5.6
ANOVA	10	Zero	Medium	Strength	5.5
ANOVA	10	Zero	Medium	Power	5.7
ANOVA	10	Zero	Medium	Sprint	5.8
ANOVA	10	Zero	Large	Strength	5.6
ANOVA	10	Zero	Large	Power	5.7
ANOVA	10	Zero	Large	Sprint	5.8
ANOVA	10	Small	Small	Strength	5.5
ANOVA	10	Small	Small	Power	5.7
ANOVA	10	Small	Small	Sprint	5.6
ANOVA	10	Small	Medium	Strength	5.7
ANOVA	10	Small	Medium	Power	5.7
ANOVA	10	Small	Medium	Sprint	5.6
ANOVA	10	Small	Large	Strength	5.6
ANOVA	10	Small	Large	Power	5.8
ANOVA	10	Small	Large	Sprint	5.7
ANOVA	10	Medium	Small	Strength	5.6
ANOVA	10	Medium	Small	Power	5.5
ANOVA	10	Medium	Small	Sprint	5.6
ANOVA	10	Medium	Medium	Strength	5.4
ANOVA	10	Medium	Medium	Power	5.6
ANOVA	10	Medium	Medium	Sprint	5.7
ANOVA	10	Medium	Large	Strength	5.7
ANOVA	10	Medium	Large	Power	5.7
ANOVA	10	Medium	Large	Sprint	5.7
ANOVA	15	Zero	Small	Strength	5.3
ANOVA	15	Zero	Small	Power	5.5
ANOVA	15	Zero	Small	Sprint	5.1
ANOVA	15	Zero	Medium	Strength	5.3
ANOVA	15	Zero	Medium	Power	5.4
ANOVA	15	Zero	Medium	Sprint	5.3
ANOVA	15	Zero	Large	Strength	5.3
ANOVA	15	Zero	Large	Power	5.2
ANOVA	15	Zero	Large	Sprint	5.5

ANOVA	15	Small	Small	Strength	5.4
ANOVA	15	Small	Small	Power	5.4
ANOVA	15	Small	Small	Sprint	5.3
ANOVA	15	Small	Medium	Strength	5.3
ANOVA	15	Small	Medium	Power	5.1
ANOVA	15	Small	Medium	Sprint	5.3
ANOVA	15	Small	Large	Strength	5.4
ANOVA	15	Small	Large	Power	5.3
ANOVA	15	Small	Large	Sprint	5.5
ANOVA	15	Medium	Small	Strength	5.4
ANOVA	15	Medium	Small	Power	5.1
ANOVA	15	Medium	Small	Sprint	5.2
ANOVA	15	Medium	Medium	Strength	5.5
ANOVA	15	Medium	Medium	Power	5.2
ANOVA	15	Medium	Medium	Sprint	5.2
ANOVA	15	Medium	Large	Strength	5.3
ANOVA	15	Medium	Large	Power	5.3
ANOVA	15	Medium	Large	Sprint	5.3
ANOVA	25	Zero	Small	Strength	5.2
ANOVA	25	Zero	Small	Power	5.4
ANOVA	25	Zero	Small	Sprint	5.3
ANOVA	25	Zero	Medium	Strength	5.3
ANOVA	25	Zero	Medium	Power	5.2
ANOVA	25	Zero	Medium	Sprint	5.4
ANOVA	25	Zero	Large	Strength	5.3
ANOVA	25	Zero	Large	Power	5.2
ANOVA	25	Zero	Large	Sprint	5.1
ANOVA	25	Small	Small	Strength	5.3
ANOVA	25	Small	Small	Power	5.5
ANOVA	25	Small	Small	Sprint	5.4
ANOVA	25	Small	Medium	Strength	5.3
ANOVA	25	Small	Medium	Power	5.3
ANOVA	25	Small	Medium	Sprint	5.5
ANOVA	25	Small	Large	Strength	5.3
ANOVA	25	Small	Large	Power	5.4
ANOVA	25	Small	Large	Sprint	5.4
ANOVA	25	Medium	Small	Strength	5.2
ANOVA	25	Medium	Small	Power	5.4
ANOVA	25	Medium	Small	Sprint	5.4
ANOVA	25	Medium	Medium	Strength	5.2
ANOVA	25	Medium	Medium	Power	5.4
ANOVA	25	Medium	Medium	Sprint	5.5
ANOVA	25	Medium	Large	Strength	5.4
ANOVA	25	Medium	Large	Power	5.3
ANOVA	25	Medium	Large	Sprint	5.4
ANOVA	50	Zero	Small	Strength	5.1
ANOVA	50	Zero	Small	Power	5.2
ANOVA	50	Zero	Small	Sprint	5.1
ANOVA	50	Zero	Medium	Strength	5.2
ANOVA	50	Zero	Medium	Power	5.1

ANOVA	50	Zero	Medium	Sprint	5.2
ANOVA	50	Zero	Large	Strength	5.2
ANOVA	50	Zero	Large	Power	5.2
ANOVA	50	Zero	Large	Sprint	5.1
ANOVA	50	Small	Small	Strength	5
ANOVA	50	Small	Small	Power	5.1
ANOVA	50	Small	Small	Sprint	5
ANOVA	50	Small	Medium	Strength	5.1
ANOVA	50	Small	Medium	Power	5.1
ANOVA	50	Small	Medium	Sprint	5
ANOVA	50	Small	Large	Strength	5
ANOVA	50	Small	Large	Power	5.1
ANOVA	50	Small	Large	Sprint	5.1
ANOVA	50	Medium	Small	Strength	5
ANOVA	50	Medium	Small	Power	5
ANOVA	50	Medium	Small	Sprint	5
ANOVA	50	Medium	Medium	Strength	5
ANOVA	50	Medium	Medium	Power	5
ANOVA	50	Medium	Medium	Sprint	5.2
ANOVA	50	Medium	Large	Strength	5
ANOVA	50	Medium	Large	Power	5
ANOVA	50	Medium	Large	Sprint	5
T-Test	10	Zero	Small	Strength	5.2
T-Test	10	Zero	Small	Power	5.1
T-Test	10	Zero	Small	Sprint	4.9
T-Test	10	Zero	Medium	Strength	5
T-Test	10	Zero	Medium	Power	5.1
T-Test	10	Zero	Medium	Sprint	4.8
T-Test	10	Zero	Large	Strength	5.2
T-Test	10	Zero	Large	Power	5.1
T-Test	10	Zero	Large	Sprint	5
T-Test	10	Small	Small	Strength	5.2
T-Test	10	Small	Small	Power	5.1
T-Test	10	Small	Small	Sprint	5
T-Test	10	Small	Medium	Strength	5.1
T-Test	10	Small	Medium	Power	5.1
T-Test	10	Small	Medium	Sprint	4.8
T-Test	10	Small	Large	Strength	4.9
T-Test	10	Small	Large	Power	5.2
T-Test	10	Small	Large	Sprint	4.9
T-Test	10	Medium	Small	Strength	5.1
T-Test	10	Medium	Small	Power	5.1
T-Test	10	Medium	Small	Sprint	4.9
T-Test	10	Medium	Medium	Strength	5
T-Test	10	Medium	Medium	Power	5.2
T-Test	10	Medium	Medium	Sprint	4.9
T-Test	10	Medium	Large	Strength	5
T-Test	10	Medium	Large	Power	5.1
T-Test	10	Medium	Large	Sprint	5
T-Test	15	Zero	Small	Strength	4.7

T-Test	15	Zero	Small	Power	5.1
T-Test	15	Zero	Small	Sprint	4.5
T-Test	15	Zero	Medium	Strength	4.6
T-Test	15	Zero	Medium	Power	5.2
T-Test	15	Zero	Medium	Sprint	4.5
T-Test	15	Zero	Large	Strength	4.8
T-Test	15	Zero	Large	Power	5
T-Test	15	Zero	Large	Sprint	4.6
T-Test	15	Small	Small	Strength	4.7
T-Test	15	Small	Small	Power	5.2
T-Test	15	Small	Small	Sprint	4.4
T-Test	15	Small	Medium	Strength	4.6
T-Test	15	Small	Medium	Power	5.2
T-Test	15	Small	Medium	Sprint	4.5
T-Test	15	Small	Large	Strength	4.8
T-Test	15	Small	Large	Power	5
T-Test	15	Small	Large	Sprint	4.6
T-Test	15	Medium	Small	Strength	4.7
T-Test	15	Medium	Small	Power	5.1
T-Test	15	Medium	Small	Sprint	4.4
T-Test	15	Medium	Medium	Strength	4.5
T-Test	15	Medium	Medium	Power	5.1
T-Test	15	Medium	Medium	Sprint	4.6
T-Test	15	Medium	Large	Strength	4.7
T-Test	15	Medium	Large	Power	5
T-Test	15	Medium	Large	Sprint	4.7
T-Test	25	Zero	Small	Strength	4.9
T-Test	25	Zero	Small	Power	5.1
T-Test	25	Zero	Small	Sprint	4.7
T-Test	25	Zero	Medium	Strength	4.9
T-Test	25	Zero	Medium	Power	5.1
T-Test	25	Zero	Medium	Sprint	4.8
T-Test	25	Zero	Large	Strength	4.9
T-Test	25	Zero	Large	Power	5
T-Test	25	Zero	Large	Sprint	4.6
T-Test	25	Small	Small	Strength	4.9
T-Test	25	Small	Small	Power	4.9
T-Test	25	Small	Small	Sprint	4.7
T-Test	25	Small	Medium	Strength	4.9
T-Test	25	Small	Medium	Power	5.1
T-Test	25	Small	Medium	Sprint	4.6
T-Test	25	Small	Large	Strength	4.9
T-Test	25	Small	Large	Power	5
T-Test	25	Small	Large	Sprint	4.6
T-Test	25	Medium	Small	Strength	4.9
T-Test	25	Medium	Small	Power	5
T-Test	25	Medium	Small	Sprint	4.8
T-Test	25	Medium	Medium	Strength	4.8
T-Test	25	Medium	Medium	Power	5.1
T-Test	25	Medium	Medium	Sprint	4.7

T-Test	25	Medium	Large	Strength	4.9
T-Test	25	Medium	Large	Power	5
T-Test	25	Medium	Large	Sprint	5
T-Test	50	Zero	Small	Strength	5.2
T-Test	50	Zero	Small	Power	4.8
T-Test	50	Zero	Small	Sprint	5.1
T-Test	50	Zero	Medium	Strength	5.3
T-Test	50	Zero	Medium	Power	4.8
T-Test	50	Zero	Medium	Sprint	5.1
T-Test	50	Zero	Large	Strength	5.2
T-Test	50	Zero	Large	Power	4.7
T-Test	50	Zero	Large	Sprint	5
T-Test	50	Small	Small	Strength	5.3
T-Test	50	Small	Small	Power	4.9
T-Test	50	Small	Small	Sprint	5.1
T-Test	50	Small	Medium	Strength	5.2
T-Test	50	Small	Medium	Power	4.8
T-Test	50	Small	Medium	Sprint	5.2
T-Test	50	Small	Large	Strength	5.2
T-Test	50	Small	Large	Power	4.9
T-Test	50	Small	Large	Sprint	5
T-Test	50	Medium	Small	Strength	5.3
T-Test	50	Medium	Small	Power	4.9
T-Test	50	Medium	Small	Sprint	5.1
T-Test	50	Medium	Medium	Strength	5.3
T-Test	50	Medium	Medium	Power	4.9
T-Test	50	Medium	Medium	Sprint	5.2
T-Test	50	Medium	Large	Strength	5.1
T-Test	50	Medium	Large	Power	4.7
T-Test	50	Medium	Large	Sprint	5.3

Small ATE and Zero Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	7.2
ANCOVA	10	Zero	Small	Power	7.6
ANCOVA	10	Zero	Small	Sprint	8.9
ANCOVA	10	Zero	Medium	Strength	6.6
ANCOVA	10	Zero	Medium	Power	7.1
ANCOVA	10	Zero	Medium	Sprint	7.9
ANCOVA	10	Zero	Large	Strength	6.3
ANCOVA	10	Zero	Large	Power	6.4
ANCOVA	10	Zero	Large	Sprint	6.7
ANCOVA	10	Small	Small	Strength	7.9
ANCOVA	10	Small	Small	Power	8.5
ANCOVA	10	Small	Small	Sprint	10.3
ANCOVA	10	Small	Medium	Strength	7.4
ANCOVA	10	Small	Medium	Power	7.9
ANCOVA	10	Small	Medium	Sprint	8.8
ANCOVA	10	Small	Large	Strength	6.5
ANCOVA	10	Small	Large	Power	6.7
ANCOVA	10	Small	Large	Sprint	6.9

ANCOVA	10	Medium	Small	Strength	9.1
ANCOVA	10	Medium	Small	Power	10.1
ANCOVA	10	Medium	Small	Sprint	13
ANCOVA	10	Medium	Medium	Strength	8.2
ANCOVA	10	Medium	Medium	Power	8.9
ANCOVA	10	Medium	Medium	Sprint	10.1
ANCOVA	10	Medium	Large	Strength	7
ANCOVA	10	Medium	Large	Power	7.2
ANCOVA	10	Medium	Large	Sprint	7.2
ANCOVA	15	Zero	Small	Strength	8.2
ANCOVA	15	Zero	Small	Power	9.2
ANCOVA	15	Zero	Small	Sprint	11.4
ANCOVA	15	Zero	Medium	Strength	7.5
ANCOVA	15	Zero	Medium	Power	8.3
ANCOVA	15	Zero	Medium	Sprint	9.5
ANCOVA	15	Zero	Large	Strength	6.6
ANCOVA	15	Zero	Large	Power	7.2
ANCOVA	15	Zero	Large	Sprint	7.4
ANCOVA	15	Small	Small	Strength	9.2
ANCOVA	15	Small	Small	Power	10.6
ANCOVA	15	Small	Small	Sprint	13.5
ANCOVA	15	Small	Medium	Strength	8.4
ANCOVA	15	Small	Medium	Power	9.6
ANCOVA	15	Small	Medium	Sprint	11.4
ANCOVA	15	Small	Large	Strength	7.2
ANCOVA	15	Small	Large	Power	7.7
ANCOVA	15	Small	Large	Sprint	8.1
ANCOVA	15	Medium	Small	Strength	11.4
ANCOVA	15	Medium	Small	Power	13.5
ANCOVA	15	Medium	Small	Sprint	18.1
ANCOVA	15	Medium	Medium	Strength	10
ANCOVA	15	Medium	Medium	Power	11.2
ANCOVA	15	Medium	Medium	Sprint	13.5
ANCOVA	15	Medium	Large	Strength	8
ANCOVA	15	Medium	Large	Power	8.5
ANCOVA	15	Medium	Large	Sprint	8.6
ANCOVA	25	Zero	Small	Strength	10.8
ANCOVA	25	Zero	Small	Power	13.2
ANCOVA	25	Zero	Small	Sprint	17
ANCOVA	25	Zero	Medium	Strength	9.9
ANCOVA	25	Zero	Medium	Power	11.4
ANCOVA	25	Zero	Medium	Sprint	13.7
ANCOVA	25	Zero	Large	Strength	8
ANCOVA	25	Zero	Large	Power	8.9
ANCOVA	25	Zero	Large	Sprint	9.6
ANCOVA	25	Small	Small	Strength	12.8
ANCOVA	25	Small	Small	Power	15.9
ANCOVA	25	Small	Small	Sprint	20.9
ANCOVA	25	Small	Medium	Strength	11.5
ANCOVA	25	Small	Medium	Power	13.5

ANCOVA	25	Small	Medium	Sprint	16.4
ANCOVA	25	Small	Large	Strength	9.3
ANCOVA	25	Small	Large	Power	9.9
ANCOVA	25	Small	Large	Sprint	10.9
ANCOVA	25	Medium	Small	Strength	16.7
ANCOVA	25	Medium	Small	Power	20.9
ANCOVA	25	Medium	Small	Sprint	28.6
ANCOVA	25	Medium	Medium	Strength	14.4
ANCOVA	25	Medium	Medium	Power	17
ANCOVA	25	Medium	Medium	Sprint	20.4
ANCOVA	25	Medium	Large	Strength	10.6
ANCOVA	25	Medium	Large	Power	11.3
ANCOVA	25	Medium	Large	Sprint	11.7
ANCOVA	50	Zero	Small	Strength	16.6
ANCOVA	50	Zero	Small	Power	20.9
ANCOVA	50	Zero	Small	Sprint	29.5
ANCOVA	50	Zero	Medium	Strength	14.9
ANCOVA	50	Zero	Medium	Power	18.2
ANCOVA	50	Zero	Medium	Sprint	22.7
ANCOVA	50	Zero	Large	Strength	11.5
ANCOVA	50	Zero	Large	Power	13.2
ANCOVA	50	Zero	Large	Sprint	14.3
ANCOVA	50	Small	Small	Strength	20.5
ANCOVA	50	Small	Small	Power	26.8
ANCOVA	50	Small	Small	Sprint	37.2
ANCOVA	50	Small	Medium	Strength	18.2
ANCOVA	50	Small	Medium	Power	22.4
ANCOVA	50	Small	Medium	Sprint	28.3
ANCOVA	50	Small	Large	Strength	13.8
ANCOVA	50	Small	Large	Power	15.4
ANCOVA	50	Small	Large	Sprint	17.2
ANCOVA	50	Medium	Small	Strength	27.9
ANCOVA	50	Medium	Small	Power	37.1
ANCOVA	50	Medium	Small	Sprint	50.9
ANCOVA	50	Medium	Medium	Strength	23.5
ANCOVA	50	Medium	Medium	Power	29
ANCOVA	50	Medium	Medium	Sprint	36.1
ANCOVA	50	Medium	Large	Strength	16.6
ANCOVA	50	Medium	Large	Power	18.4
ANCOVA	50	Medium	Large	Sprint	19.2
ANOVA	10	Zero	Small	Strength	8.1
ANOVA	10	Zero	Small	Power	8.7
ANOVA	10	Zero	Small	Sprint	10.3
ANOVA	10	Zero	Medium	Strength	7.7
ANOVA	10	Zero	Medium	Power	8.3
ANOVA	10	Zero	Medium	Sprint	9
ANOVA	10	Zero	Large	Strength	7
ANOVA	10	Zero	Large	Power	7
ANOVA	10	Zero	Large	Sprint	7.5
ANOVA	10	Small	Small	Strength	7.9

ANOVA	10	Small	Small	Power	8.7
ANOVA	10	Small	Small	Sprint	10.6
ANOVA	10	Small	Medium	Strength	7.6
ANOVA	10	Small	Medium	Power	7.9
ANOVA	10	Small	Medium	Sprint	9.1
ANOVA	10	Small	Large	Strength	7
ANOVA	10	Small	Large	Power	7.1
ANOVA	10	Small	Large	Sprint	7.4
ANOVA	10	Medium	Small	Strength	7.6
ANOVA	10	Medium	Small	Power	8.7
ANOVA	10	Medium	Small	Sprint	10.6
ANOVA	10	Medium	Medium	Strength	7.6
ANOVA	10	Medium	Medium	Power	8
ANOVA	10	Medium	Medium	Sprint	9.2
ANOVA	10	Medium	Large	Strength	6.8
ANOVA	10	Medium	Large	Power	6.9
ANOVA	10	Medium	Large	Sprint	7.5
ANOVA	15	Zero	Small	Strength	8.9
ANOVA	15	Zero	Small	Power	10.1
ANOVA	15	Zero	Small	Sprint	12.4
ANOVA	15	Zero	Medium	Strength	8.3
ANOVA	15	Zero	Medium	Power	9.2
ANOVA	15	Zero	Medium	Sprint	10.5
ANOVA	15	Zero	Large	Strength	7.3
ANOVA	15	Zero	Large	Power	7.5
ANOVA	15	Zero	Large	Sprint	8
ANOVA	15	Small	Small	Strength	8.8
ANOVA	15	Small	Small	Power	9.8
ANOVA	15	Small	Small	Sprint	12.8
ANOVA	15	Small	Medium	Strength	8.4
ANOVA	15	Small	Medium	Power	8.8
ANOVA	15	Small	Medium	Sprint	10.7
ANOVA	15	Small	Large	Strength	7.3
ANOVA	15	Small	Large	Power	7.6
ANOVA	15	Small	Large	Sprint	7.9
ANOVA	15	Medium	Small	Strength	8.8
ANOVA	15	Medium	Small	Power	9.8
ANOVA	15	Medium	Small	Sprint	12.7
ANOVA	15	Medium	Medium	Strength	8.2
ANOVA	15	Medium	Medium	Power	9
ANOVA	15	Medium	Medium	Sprint	10.6
ANOVA	15	Medium	Large	Strength	7.2
ANOVA	15	Medium	Large	Power	7.5
ANOVA	15	Medium	Large	Sprint	8.1
ANOVA	25	Zero	Small	Strength	11.5
ANOVA	25	Zero	Small	Power	13.9
ANOVA	25	Zero	Small	Sprint	18
ANOVA	25	Zero	Medium	Strength	10.4
ANOVA	25	Zero	Medium	Power	12.1
ANOVA	25	Zero	Medium	Sprint	14.3

ANOVA	25	Zero	Large	Strength	8.4
ANOVA	25	Zero	Large	Power	8.9
ANOVA	25	Zero	Large	Sprint	9.8
ANOVA	25	Small	Small	Strength	11.2
ANOVA	25	Small	Small	Power	13.5
ANOVA	25	Small	Small	Sprint	18.1
ANOVA	25	Small	Medium	Strength	10.3
ANOVA	25	Small	Medium	Power	11.9
ANOVA	25	Small	Medium	Sprint	14.3
ANOVA	25	Small	Large	Strength	8.4
ANOVA	25	Small	Large	Power	9.1
ANOVA	25	Small	Large	Sprint	9.9
ANOVA	25	Medium	Small	Strength	11.1
ANOVA	25	Medium	Small	Power	13.3
ANOVA	25	Medium	Small	Sprint	17.8
ANOVA	25	Medium	Medium	Strength	10.2
ANOVA	25	Medium	Medium	Power	11.8
ANOVA	25	Medium	Medium	Sprint	14
ANOVA	25	Medium	Large	Strength	8.3
ANOVA	25	Medium	Large	Power	9
ANOVA	25	Medium	Large	Sprint	9.9
ANOVA	50	Zero	Small	Strength	17.2
ANOVA	50	Zero	Small	Power	21.6
ANOVA	50	Zero	Small	Sprint	30.1
ANOVA	50	Zero	Medium	Strength	15.3
ANOVA	50	Zero	Medium	Power	18.4
ANOVA	50	Zero	Medium	Sprint	23.2
ANOVA	50	Zero	Large	Strength	11.4
ANOVA	50	Zero	Large	Power	12.6
ANOVA	50	Zero	Large	Sprint	14
ANOVA	50	Small	Small	Strength	16.5
ANOVA	50	Small	Small	Power	21.2
ANOVA	50	Small	Small	Sprint	29.8
ANOVA	50	Small	Medium	Strength	14.7
ANOVA	50	Small	Medium	Power	17.7
ANOVA	50	Small	Medium	Sprint	22.5
ANOVA	50	Small	Large	Strength	11.3
ANOVA	50	Small	Large	Power	12.3
ANOVA	50	Small	Large	Sprint	13.7
ANOVA	50	Medium	Small	Strength	16.4
ANOVA	50	Medium	Small	Power	20.9
ANOVA	50	Medium	Small	Sprint	29.8
ANOVA	50	Medium	Medium	Strength	14.6
ANOVA	50	Medium	Medium	Power	17.9
ANOVA	50	Medium	Medium	Sprint	22.7
ANOVA	50	Medium	Large	Strength	10.8
ANOVA	50	Medium	Large	Power	12.6
ANOVA	50	Medium	Large	Sprint	14
T-Test	10	Zero	Small	Strength	5.9
T-Test	10	Zero	Small	Power	5.7

T-Test	10	Zero	Small	Sprint	5.8
T-Test	10	Zero	Medium	Strength	6
T-Test	10	Zero	Medium	Power	5.7
T-Test	10	Zero	Medium	Sprint	5.7
T-Test	10	Zero	Large	Strength	5.7
T-Test	10	Zero	Large	Power	5.8
T-Test	10	Zero	Large	Sprint	5.6
T-Test	10	Small	Small	Strength	6.5
T-Test	10	Small	Small	Power	6.4
T-Test	10	Small	Small	Sprint	6.4
T-Test	10	Small	Medium	Strength	6.4
T-Test	10	Small	Medium	Power	6.5
T-Test	10	Small	Medium	Sprint	6.2
T-Test	10	Small	Large	Strength	6.3
T-Test	10	Small	Large	Power	6.2
T-Test	10	Small	Large	Sprint	6
T-Test	10	Medium	Small	Strength	7.5
T-Test	10	Medium	Small	Power	7.1
T-Test	10	Medium	Small	Sprint	7
T-Test	10	Medium	Medium	Strength	7.2
T-Test	10	Medium	Medium	Power	7.1
T-Test	10	Medium	Medium	Sprint	6.7
T-Test	10	Medium	Large	Strength	6.6
T-Test	10	Medium	Large	Power	6.7
T-Test	10	Medium	Large	Sprint	6.4
T-Test	15	Zero	Small	Strength	6
T-Test	15	Zero	Small	Power	6.4
T-Test	15	Zero	Small	Sprint	6
T-Test	15	Zero	Medium	Strength	6
T-Test	15	Zero	Medium	Power	6.3
T-Test	15	Zero	Medium	Sprint	5.9
T-Test	15	Zero	Large	Strength	5.8
T-Test	15	Zero	Large	Power	6.3
T-Test	15	Zero	Large	Sprint	5.8
T-Test	15	Small	Small	Strength	7.1
T-Test	15	Small	Small	Power	7.3
T-Test	15	Small	Small	Sprint	7.1
T-Test	15	Small	Medium	Strength	7
T-Test	15	Small	Medium	Power	7.3
T-Test	15	Small	Medium	Sprint	6.8
T-Test	15	Small	Large	Strength	6.4
T-Test	15	Small	Large	Power	7
T-Test	15	Small	Large	Sprint	6.4
T-Test	15	Medium	Small	Strength	8.5
T-Test	15	Medium	Small	Power	8.6
T-Test	15	Medium	Small	Sprint	7.8
T-Test	15	Medium	Medium	Strength	8.2
T-Test	15	Medium	Medium	Power	8.3
T-Test	15	Medium	Medium	Sprint	7.7
T-Test	15	Medium	Large	Strength	7.2

T-Test	15	Medium	Large	Power	7.5
T-Test	15	Medium	Large	Sprint	7
T-Test	25	Zero	Small	Strength	7.2
T-Test	25	Zero	Small	Power	7.4
T-Test	25	Zero	Small	Sprint	7.5
T-Test	25	Zero	Medium	Strength	7
T-Test	25	Zero	Medium	Power	7.4
T-Test	25	Zero	Medium	Sprint	7.2
T-Test	25	Zero	Large	Strength	6.8
T-Test	25	Zero	Large	Power	6.9
T-Test	25	Zero	Large	Sprint	7
T-Test	25	Small	Small	Strength	9.1
T-Test	25	Small	Small	Power	9.3
T-Test	25	Small	Small	Sprint	9.1
T-Test	25	Small	Medium	Strength	8.9
T-Test	25	Small	Medium	Power	9.1
T-Test	25	Small	Medium	Sprint	8.9
T-Test	25	Small	Large	Strength	8
T-Test	25	Small	Large	Power	8.2
T-Test	25	Small	Large	Sprint	8.1
T-Test	25	Medium	Small	Strength	11.6
T-Test	25	Medium	Small	Power	11.5
T-Test	25	Medium	Small	Sprint	10.6
T-Test	25	Medium	Medium	Strength	11
T-Test	25	Medium	Medium	Power	10.9
T-Test	25	Medium	Medium	Sprint	10.2
T-Test	25	Medium	Large	Strength	9.1
T-Test	25	Medium	Large	Power	9.4
T-Test	25	Medium	Large	Sprint	9.1
T-Test	50	Zero	Small	Strength	9.5
T-Test	50	Zero	Small	Power	9.8
T-Test	50	Zero	Small	Sprint	10.5
T-Test	50	Zero	Medium	Strength	9.5
T-Test	50	Zero	Medium	Power	9.6
T-Test	50	Zero	Medium	Sprint	10.3
T-Test	50	Zero	Large	Strength	8.9
T-Test	50	Zero	Large	Power	9.1
T-Test	50	Zero	Large	Sprint	9.8
T-Test	50	Small	Small	Strength	13.4
T-Test	50	Small	Small	Power	13.7
T-Test	50	Small	Small	Sprint	14
T-Test	50	Small	Medium	Strength	13
T-Test	50	Small	Medium	Power	13.1
T-Test	50	Small	Medium	Sprint	13.6
T-Test	50	Small	Large	Strength	11.4
T-Test	50	Small	Large	Power	11.6
T-Test	50	Small	Large	Sprint	11.9
T-Test	50	Medium	Small	Strength	18.3
T-Test	50	Medium	Small	Power	18.1
T-Test	50	Medium	Small	Sprint	17.2

T-Test	50	Medium	Medium	Strength	17.1
T-Test	50	Medium	Medium	Power	17
T-Test	50	Medium	Medium	Sprint	16.2
T-Test	50	Medium	Large	Strength	14
T-Test	50	Medium	Large	Power	14
T-Test	50	Medium	Large	Sprint	13.6

Small ATE and Positive Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	7.1
ANCOVA	10	Zero	Small	Power	7.6
ANCOVA	10	Zero	Small	Sprint	9.3
ANCOVA	10	Zero	Medium	Strength	7.5
ANCOVA	10	Zero	Medium	Power	8
ANCOVA	10	Zero	Medium	Sprint	9.3
ANCOVA	10	Zero	Large	Strength	8
ANCOVA	10	Zero	Large	Power	8.6
ANCOVA	10	Zero	Large	Sprint	9.2
ANCOVA	10	Small	Small	Strength	7.9
ANCOVA	10	Small	Small	Power	8.6
ANCOVA	10	Small	Small	Sprint	10.5
ANCOVA	10	Small	Medium	Strength	8
ANCOVA	10	Small	Medium	Power	9
ANCOVA	10	Small	Medium	Sprint	10.1
ANCOVA	10	Small	Large	Strength	8.1
ANCOVA	10	Small	Large	Power	9
ANCOVA	10	Small	Large	Sprint	9.4
ANCOVA	10	Medium	Small	Strength	9.1
ANCOVA	10	Medium	Small	Power	10.2
ANCOVA	10	Medium	Small	Sprint	13.3
ANCOVA	10	Medium	Medium	Strength	9
ANCOVA	10	Medium	Medium	Power	10
ANCOVA	10	Medium	Medium	Sprint	12
ANCOVA	10	Medium	Large	Strength	8.4
ANCOVA	10	Medium	Large	Power	9.1
ANCOVA	10	Medium	Large	Sprint	10.1
ANCOVA	15	Zero	Small	Strength	8.2
ANCOVA	15	Zero	Small	Power	9.2
ANCOVA	15	Zero	Small	Sprint	11.6
ANCOVA	15	Zero	Medium	Strength	8.7
ANCOVA	15	Zero	Medium	Power	9.8
ANCOVA	15	Zero	Medium	Sprint	11.7
ANCOVA	15	Zero	Large	Strength	9.9
ANCOVA	15	Zero	Large	Power	10.7
ANCOVA	15	Zero	Large	Sprint	11.9
ANCOVA	15	Small	Small	Strength	9.2
ANCOVA	15	Small	Small	Power	10.6
ANCOVA	15	Small	Small	Sprint	13.8
ANCOVA	15	Small	Medium	Strength	9.4
ANCOVA	15	Small	Medium	Power	10.8
ANCOVA	15	Small	Medium	Sprint	13.3

ANCOVA	15	Small	Large	Strength	9.6
ANCOVA	15	Small	Large	Power	11
ANCOVA	15	Small	Large	Sprint	12.3
ANCOVA	15	Medium	Small	Strength	11.2
ANCOVA	15	Medium	Small	Power	13.4
ANCOVA	15	Medium	Small	Sprint	18.2
ANCOVA	15	Medium	Medium	Strength	10.9
ANCOVA	15	Medium	Medium	Power	12.6
ANCOVA	15	Medium	Medium	Sprint	16
ANCOVA	15	Medium	Large	Strength	10.1
ANCOVA	15	Medium	Large	Power	11.8
ANCOVA	15	Medium	Large	Sprint	13
ANCOVA	25	Zero	Small	Strength	10.8
ANCOVA	25	Zero	Small	Power	13.4
ANCOVA	25	Zero	Small	Sprint	17.5
ANCOVA	25	Zero	Medium	Strength	11.7
ANCOVA	25	Zero	Medium	Power	13.8
ANCOVA	25	Zero	Medium	Sprint	17.1
ANCOVA	25	Zero	Large	Strength	13.8
ANCOVA	25	Zero	Large	Power	15.3
ANCOVA	25	Zero	Large	Sprint	17.3
ANCOVA	25	Small	Small	Strength	12.7
ANCOVA	25	Small	Small	Power	15.9
ANCOVA	25	Small	Small	Sprint	21.1
ANCOVA	25	Small	Medium	Strength	13
ANCOVA	25	Small	Medium	Power	15.7
ANCOVA	25	Small	Medium	Sprint	19.6
ANCOVA	25	Small	Large	Strength	13.6
ANCOVA	25	Small	Large	Power	15.6
ANCOVA	25	Small	Large	Sprint	17.8
ANCOVA	25	Medium	Small	Strength	16.3
ANCOVA	25	Medium	Small	Power	20.9
ANCOVA	25	Medium	Small	Sprint	28.7
ANCOVA	25	Medium	Medium	Strength	15.8
ANCOVA	25	Medium	Medium	Power	19.2
ANCOVA	25	Medium	Medium	Sprint	24
ANCOVA	25	Medium	Large	Strength	14.3
ANCOVA	25	Medium	Large	Power	17.1
ANCOVA	25	Medium	Large	Sprint	18.8
ANCOVA	50	Zero	Small	Strength	16.6
ANCOVA	50	Zero	Small	Power	21.2
ANCOVA	50	Zero	Small	Sprint	29.9
ANCOVA	50	Zero	Medium	Strength	18.2
ANCOVA	50	Zero	Medium	Power	22.9
ANCOVA	50	Zero	Medium	Sprint	29.2
ANCOVA	50	Zero	Large	Strength	22.4
ANCOVA	50	Zero	Large	Power	26.1
ANCOVA	50	Zero	Large	Sprint	29.9
ANCOVA	50	Small	Small	Strength	20.4
ANCOVA	50	Small	Small	Power	26.4

ANCOVA	50	Small	Small	Sprint	37.2
ANCOVA	50	Small	Medium	Strength	20.8
ANCOVA	50	Small	Medium	Power	26.5
ANCOVA	50	Small	Medium	Sprint	34.2
ANCOVA	50	Small	Large	Strength	22
ANCOVA	50	Small	Large	Power	26.3
ANCOVA	50	Small	Large	Sprint	31.1
ANCOVA	50	Medium	Small	Strength	27.3
ANCOVA	50	Medium	Small	Power	36
ANCOVA	50	Medium	Small	Sprint	50.8
ANCOVA	50	Medium	Medium	Strength	26.5
ANCOVA	50	Medium	Medium	Power	33.2
ANCOVA	50	Medium	Medium	Sprint	42.7
ANCOVA	50	Medium	Large	Strength	23.9
ANCOVA	50	Medium	Large	Power	29.1
ANCOVA	50	Medium	Large	Sprint	33
ANOVA	10	Zero	Small	Strength	8.2
ANOVA	10	Zero	Small	Power	8.6
ANOVA	10	Zero	Small	Sprint	10.4
ANOVA	10	Zero	Medium	Strength	7.7
ANOVA	10	Zero	Medium	Power	8.2
ANOVA	10	Zero	Medium	Sprint	9.1
ANOVA	10	Zero	Large	Strength	6.9
ANOVA	10	Zero	Large	Power	7.1
ANOVA	10	Zero	Large	Sprint	7.5
ANOVA	10	Small	Small	Strength	3.2
ANOVA	10	Small	Small	Power	3.4
ANOVA	10	Small	Small	Sprint	3.6
ANOVA	10	Small	Medium	Strength	3.7
ANOVA	10	Small	Medium	Power	3.8
ANOVA	10	Small	Medium	Sprint	3.9
ANOVA	10	Small	Large	Strength	4.2
ANOVA	10	Small	Large	Power	4.6
ANOVA	10	Small	Large	Sprint	4.9
ANOVA	10	Medium	Small	Strength	1.9
ANOVA	10	Medium	Small	Power	1.8
ANOVA	10	Medium	Small	Sprint	1.5
ANOVA	10	Medium	Medium	Strength	2.4
ANOVA	10	Medium	Medium	Power	2.6
ANOVA	10	Medium	Medium	Sprint	2.5
ANOVA	10	Medium	Large	Strength	3.5
ANOVA	10	Medium	Large	Power	3.7
ANOVA	10	Medium	Large	Sprint	4
ANOVA	15	Zero	Small	Strength	9
ANOVA	15	Zero	Small	Power	9.9
ANOVA	15	Zero	Small	Sprint	12.6
ANOVA	15	Zero	Medium	Strength	8.4
ANOVA	15	Zero	Medium	Power	9.2
ANOVA	15	Zero	Medium	Sprint	10.6
ANOVA	15	Zero	Large	Strength	7.2

ANOVA	15	Zero	Large	Power	7.7
ANOVA	15	Zero	Large	Sprint	8
ANOVA	15	Small	Small	Strength	2.8
ANOVA	15	Small	Small	Power	2.9
ANOVA	15	Small	Small	Sprint	3
ANOVA	15	Small	Medium	Strength	3.4
ANOVA	15	Small	Medium	Power	3.5
ANOVA	15	Small	Medium	Sprint	3.6
ANOVA	15	Small	Large	Strength	3.8
ANOVA	15	Small	Large	Power	4.3
ANOVA	15	Small	Large	Sprint	4.6
ANOVA	15	Medium	Small	Strength	2.1
ANOVA	15	Medium	Small	Power	1.8
ANOVA	15	Medium	Small	Sprint	1.2
ANOVA	15	Medium	Medium	Strength	2.8
ANOVA	15	Medium	Medium	Power	2.3
ANOVA	15	Medium	Medium	Sprint	2.2
ANOVA	15	Medium	Large	Strength	3.6
ANOVA	15	Medium	Large	Power	3.6
ANOVA	15	Medium	Large	Sprint	3.8
ANOVA	25	Zero	Small	Strength	11.4
ANOVA	25	Zero	Small	Power	13.8
ANOVA	25	Zero	Small	Sprint	18
ANOVA	25	Zero	Medium	Strength	10.5
ANOVA	25	Zero	Medium	Power	11.9
ANOVA	25	Zero	Medium	Sprint	14.2
ANOVA	25	Zero	Large	Strength	8.3
ANOVA	25	Zero	Large	Power	9
ANOVA	25	Zero	Large	Sprint	9.8
ANOVA	25	Small	Small	Strength	2.8
ANOVA	25	Small	Small	Power	2.9
ANOVA	25	Small	Small	Sprint	3.1
ANOVA	25	Small	Medium	Strength	3.2
ANOVA	25	Small	Medium	Power	3.4
ANOVA	25	Small	Medium	Sprint	3.7
ANOVA	25	Small	Large	Strength	3.9
ANOVA	25	Small	Large	Power	4.2
ANOVA	25	Small	Large	Sprint	4.5
ANOVA	25	Medium	Small	Strength	2.8
ANOVA	25	Medium	Small	Power	2
ANOVA	25	Medium	Small	Sprint	1.2
ANOVA	25	Medium	Medium	Strength	3.2
ANOVA	25	Medium	Medium	Power	2.5
ANOVA	25	Medium	Medium	Sprint	2.2
ANOVA	25	Medium	Large	Strength	3.9
ANOVA	25	Medium	Large	Power	3.7
ANOVA	25	Medium	Large	Sprint	3.8
ANOVA	50	Zero	Small	Strength	17
ANOVA	50	Zero	Small	Power	21.7
ANOVA	50	Zero	Small	Sprint	30.2

ANOVA	50	Zero	Medium	Strength	15.1
ANOVA	50	Zero	Medium	Power	18.3
ANOVA	50	Zero	Medium	Sprint	23.2
ANOVA	50	Zero	Large	Strength	11.4
ANOVA	50	Zero	Large	Power	12.7
ANOVA	50	Zero	Large	Sprint	14
ANOVA	50	Small	Small	Strength	3.2
ANOVA	50	Small	Small	Power	2.8
ANOVA	50	Small	Small	Sprint	3.1
ANOVA	50	Small	Medium	Strength	3.4
ANOVA	50	Small	Medium	Power	3.1
ANOVA	50	Small	Medium	Sprint	3.7
ANOVA	50	Small	Large	Strength	4.1
ANOVA	50	Small	Large	Power	3.9
ANOVA	50	Small	Large	Sprint	4.2
ANOVA	50	Medium	Small	Strength	5
ANOVA	50	Medium	Small	Power	2.9
ANOVA	50	Medium	Small	Sprint	1.3
ANOVA	50	Medium	Medium	Strength	5.4
ANOVA	50	Medium	Medium	Power	3.4
ANOVA	50	Medium	Medium	Sprint	2.2
ANOVA	50	Medium	Large	Strength	5.5
ANOVA	50	Medium	Large	Power	4.3
ANOVA	50	Medium	Large	Sprint	3.6
T-Test	10	Zero	Small	Strength	11.1
T-Test	10	Zero	Small	Power	11.1
T-Test	10	Zero	Small	Sprint	11.5
T-Test	10	Zero	Medium	Strength	11.1
T-Test	10	Zero	Medium	Power	11.2
T-Test	10	Zero	Medium	Sprint	11.4
T-Test	10	Zero	Large	Strength	10.5
T-Test	10	Zero	Large	Power	10.6
T-Test	10	Zero	Large	Sprint	11.1
T-Test	10	Small	Small	Strength	13.3
T-Test	10	Small	Small	Power	13.8
T-Test	10	Small	Small	Sprint	14.5
T-Test	10	Small	Medium	Strength	13.1
T-Test	10	Small	Medium	Power	13.4
T-Test	10	Small	Medium	Sprint	14
T-Test	10	Small	Large	Strength	11.3
T-Test	10	Small	Large	Power	11.9
T-Test	10	Small	Large	Sprint	12.3
T-Test	10	Medium	Small	Strength	15.7
T-Test	10	Medium	Small	Power	16.5
T-Test	10	Medium	Small	Sprint	16.8
T-Test	10	Medium	Medium	Strength	14.7
T-Test	10	Medium	Medium	Power	15.4
T-Test	10	Medium	Medium	Sprint	15.7
T-Test	10	Medium	Large	Strength	12.1
T-Test	10	Medium	Large	Power	12.6

T-Test	10	Medium	Large	Sprint	13.2
T-Test	15	Zero	Small	Strength	19.2
T-Test	15	Zero	Small	Power	20.4
T-Test	15	Zero	Small	Sprint	23.3
T-Test	15	Zero	Medium	Strength	18.8
T-Test	15	Zero	Medium	Power	19.9
T-Test	15	Zero	Medium	Sprint	22.3
T-Test	15	Zero	Large	Strength	17.3
T-Test	15	Zero	Large	Power	18.3
T-Test	15	Zero	Large	Sprint	20.1
T-Test	15	Small	Small	Strength	21.7
T-Test	15	Small	Small	Power	24.2
T-Test	15	Small	Small	Sprint	27.6
T-Test	15	Small	Medium	Strength	20.4
T-Test	15	Small	Medium	Power	22.8
T-Test	15	Small	Medium	Sprint	25.7
T-Test	15	Small	Large	Strength	17.5
T-Test	15	Small	Large	Power	19.5
T-Test	15	Small	Large	Sprint	21.1
T-Test	15	Medium	Small	Strength	25.3
T-Test	15	Medium	Small	Power	29.2
T-Test	15	Medium	Small	Sprint	32.9
T-Test	15	Medium	Medium	Strength	23.1
T-Test	15	Medium	Medium	Power	26.3
T-Test	15	Medium	Medium	Sprint	29.4
T-Test	15	Medium	Large	Strength	18.1
T-Test	15	Medium	Large	Power	20.1
T-Test	15	Medium	Large	Sprint	22.5
T-Test	25	Zero	Small	Strength	41
T-Test	25	Zero	Small	Power	47.1
T-Test	25	Zero	Small	Sprint	54.9
T-Test	25	Zero	Medium	Strength	39.5
T-Test	25	Zero	Medium	Power	45.2
T-Test	25	Zero	Medium	Sprint	51.6
T-Test	25	Zero	Large	Strength	34.9
T-Test	25	Zero	Large	Power	38.8
T-Test	25	Zero	Large	Sprint	42.9
T-Test	25	Small	Small	Strength	40.8
T-Test	25	Small	Small	Power	50.1
T-Test	25	Small	Small	Sprint	60.1
T-Test	25	Small	Medium	Strength	38.2
T-Test	25	Small	Medium	Power	46.3
T-Test	25	Small	Medium	Sprint	54.8
T-Test	25	Small	Large	Strength	31.6
T-Test	25	Small	Large	Power	37.1
T-Test	25	Small	Large	Sprint	42.6
T-Test	25	Medium	Small	Strength	46.1
T-Test	25	Medium	Small	Power	57.4
T-Test	25	Medium	Small	Sprint	68.4
T-Test	25	Medium	Medium	Strength	41.6

T-Test	25	Medium	Medium	Power	51.4
T-Test	25	Medium	Medium	Sprint	60.8
T-Test	25	Medium	Large	Strength	31.7
T-Test	25	Medium	Large	Power	37.7
T-Test	25	Medium	Large	Sprint	43.8
T-Test	50	Zero	Small	Strength	83.8
T-Test	50	Zero	Small	Power	91.1
T-Test	50	Zero	Small	Sprint	96.7
T-Test	50	Zero	Medium	Strength	81.5
T-Test	50	Zero	Medium	Power	88.9
T-Test	50	Zero	Medium	Sprint	95
T-Test	50	Zero	Large	Strength	73.8
T-Test	50	Zero	Large	Power	80.3
T-Test	50	Zero	Large	Sprint	86.8
T-Test	50	Small	Small	Strength	78.1
T-Test	50	Small	Small	Power	89.9
T-Test	50	Small	Small	Sprint	97.1
T-Test	50	Small	Medium	Strength	74.2
T-Test	50	Small	Medium	Power	86.2
T-Test	50	Small	Medium	Sprint	94.5
T-Test	50	Small	Large	Strength	62.6
T-Test	50	Small	Large	Power	73.4
T-Test	50	Small	Large	Sprint	82.7
T-Test	50	Medium	Small	Strength	82.2
T-Test	50	Medium	Small	Power	93.6
T-Test	50	Medium	Small	Sprint	98.9
T-Test	50	Medium	Medium	Strength	76.7
T-Test	50	Medium	Medium	Power	89.4
T-Test	50	Medium	Medium	Sprint	96.4
T-Test	50	Medium	Large	Strength	61
T-Test	50	Medium	Large	Power	72.9
T-Test	50	Medium	Large	Sprint	83

Small ATE and 50egative Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	6.6
ANCOVA	10	Zero	Small	Power	7.3
ANCOVA	10	Zero	Small	Sprint	8.4
ANCOVA	10	Zero	Medium	Strength	5.9
ANCOVA	10	Zero	Medium	Power	6
ANCOVA	10	Zero	Medium	Sprint	6.6
ANCOVA	10	Zero	Large	Strength	4.7
ANCOVA	10	Zero	Large	Power	4.3
ANCOVA	10	Zero	Large	Sprint	4.6
ANCOVA	10	Small	Small	Strength	7.3
ANCOVA	10	Small	Small	Power	8.4
ANCOVA	10	Small	Small	Sprint	10
ANCOVA	10	Small	Medium	Strength	6.5
ANCOVA	10	Small	Medium	Power	7
ANCOVA	10	Small	Medium	Sprint	7.6
ANCOVA	10	Small	Large	Strength	5.1

ANCOVA	10	Small	Large	Power	5.2
ANCOVA	10	Small	Large	Sprint	4.9
ANCOVA	10	Medium	Small	Strength	8.7
ANCOVA	10	Medium	Small	Power	9.8
ANCOVA	10	Medium	Small	Sprint	12.2
ANCOVA	10	Medium	Medium	Strength	7.5
ANCOVA	10	Medium	Medium	Power	7.8
ANCOVA	10	Medium	Medium	Sprint	8.4
ANCOVA	10	Medium	Large	Strength	5.6
ANCOVA	10	Medium	Large	Power	5.3
ANCOVA	10	Medium	Large	Sprint	5.2
ANCOVA	15	Zero	Small	Strength	7.8
ANCOVA	15	Zero	Small	Power	8.7
ANCOVA	15	Zero	Small	Sprint	10.6
ANCOVA	15	Zero	Medium	Strength	6.5
ANCOVA	15	Zero	Medium	Power	6.9
ANCOVA	15	Zero	Medium	Sprint	7.5
ANCOVA	15	Zero	Large	Strength	4.7
ANCOVA	15	Zero	Large	Power	4.5
ANCOVA	15	Zero	Large	Sprint	4.6
ANCOVA	15	Small	Small	Strength	8.7
ANCOVA	15	Small	Small	Power	10.2
ANCOVA	15	Small	Small	Sprint	13.1
ANCOVA	15	Small	Medium	Strength	7.4
ANCOVA	15	Small	Medium	Power	8.3
ANCOVA	15	Small	Medium	Sprint	9.2
ANCOVA	15	Small	Large	Strength	5.3
ANCOVA	15	Small	Large	Power	5.4
ANCOVA	15	Small	Large	Sprint	5.2
ANCOVA	15	Medium	Small	Strength	11
ANCOVA	15	Medium	Small	Power	12.7
ANCOVA	15	Medium	Small	Sprint	16.8
ANCOVA	15	Medium	Medium	Strength	8.9
ANCOVA	15	Medium	Medium	Power	9.7
ANCOVA	15	Medium	Medium	Sprint	10.8
ANCOVA	15	Medium	Large	Strength	6
ANCOVA	15	Medium	Large	Power	5.9
ANCOVA	15	Medium	Large	Sprint	5.5
ANCOVA	25	Zero	Small	Strength	10.4
ANCOVA	25	Zero	Small	Power	12.1
ANCOVA	25	Zero	Small	Sprint	15.5
ANCOVA	25	Zero	Medium	Strength	7.8
ANCOVA	25	Zero	Medium	Power	8.6
ANCOVA	25	Zero	Medium	Sprint	10
ANCOVA	25	Zero	Large	Strength	5
ANCOVA	25	Zero	Large	Power	4.8
ANCOVA	25	Zero	Large	Sprint	4.9
ANCOVA	25	Small	Small	Strength	11.7
ANCOVA	25	Small	Small	Power	14.5
ANCOVA	25	Small	Small	Sprint	19.4

ANCOVA	25	Small	Medium	Strength	9.6
ANCOVA	25	Small	Medium	Power	10.9
ANCOVA	25	Small	Medium	Sprint	12.5
ANCOVA	25	Small	Large	Strength	5.9
ANCOVA	25	Small	Large	Power	5.9
ANCOVA	25	Small	Large	Sprint	5.8
ANCOVA	25	Medium	Small	Strength	15.6
ANCOVA	25	Medium	Small	Power	19.2
ANCOVA	25	Medium	Small	Sprint	26.2
ANCOVA	25	Medium	Medium	Strength	12.3
ANCOVA	25	Medium	Medium	Power	13.7
ANCOVA	25	Medium	Medium	Sprint	15.8
ANCOVA	25	Medium	Large	Strength	7.1
ANCOVA	25	Medium	Large	Power	7.1
ANCOVA	25	Medium	Large	Sprint	6.4
ANCOVA	50	Zero	Small	Strength	15.2
ANCOVA	50	Zero	Small	Power	19.5
ANCOVA	50	Zero	Small	Sprint	26.7
ANCOVA	50	Zero	Medium	Strength	10.8
ANCOVA	50	Zero	Medium	Power	12.8
ANCOVA	50	Zero	Medium	Sprint	15.4
ANCOVA	50	Zero	Large	Strength	5.5
ANCOVA	50	Zero	Large	Power	5.2
ANCOVA	50	Zero	Large	Sprint	5.4
ANCOVA	50	Small	Small	Strength	18.8
ANCOVA	50	Small	Small	Power	24.4
ANCOVA	50	Small	Small	Sprint	34.2
ANCOVA	50	Small	Medium	Strength	14.4
ANCOVA	50	Small	Medium	Power	17.1
ANCOVA	50	Small	Medium	Sprint	21
ANCOVA	50	Small	Large	Strength	7.4
ANCOVA	50	Small	Large	Power	7.6
ANCOVA	50	Small	Large	Sprint	7.3
ANCOVA	50	Medium	Small	Strength	26.1
ANCOVA	50	Medium	Small	Power	34.2
ANCOVA	50	Medium	Small	Sprint	47.2
ANCOVA	50	Medium	Medium	Strength	19.6
ANCOVA	50	Medium	Medium	Power	23
ANCOVA	50	Medium	Medium	Sprint	27.4
ANCOVA	50	Medium	Large	Strength	9.8
ANCOVA	50	Medium	Large	Power	9.4
ANCOVA	50	Medium	Large	Sprint	8.8
ANOVA	10	Zero	Small	Strength	8.1
ANOVA	10	Zero	Small	Power	8.7
ANOVA	10	Zero	Small	Sprint	10.3
ANOVA	10	Zero	Medium	Strength	7.7
ANOVA	10	Zero	Medium	Power	8.2
ANOVA	10	Zero	Medium	Sprint	8.9
ANOVA	10	Zero	Large	Strength	6.9
ANOVA	10	Zero	Large	Power	7.3

ANOVA	10	Zero	Large	Sprint	7.2
ANOVA	10	Small	Small	Strength	14.1
ANOVA	10	Small	Small	Power	16.3
ANOVA	10	Small	Small	Sprint	19.5
ANOVA	10	Small	Medium	Strength	12.9
ANOVA	10	Small	Medium	Power	13.9
ANOVA	10	Small	Medium	Sprint	15.3
ANOVA	10	Small	Large	Strength	10.2
ANOVA	10	Small	Large	Power	10.6
ANOVA	10	Small	Large	Sprint	10.7
ANOVA	10	Medium	Small	Strength	17.3
ANOVA	10	Medium	Small	Power	19.5
ANOVA	10	Medium	Small	Sprint	23.3
ANOVA	10	Medium	Medium	Strength	15.4
ANOVA	10	Medium	Medium	Power	16.6
ANOVA	10	Medium	Medium	Sprint	18
ANOVA	10	Medium	Large	Strength	12.1
ANOVA	10	Medium	Large	Power	12
ANOVA	10	Medium	Large	Sprint	12.2
ANOVA	15	Zero	Small	Strength	8.8
ANOVA	15	Zero	Small	Power	10.1
ANOVA	15	Zero	Small	Sprint	12.6
ANOVA	15	Zero	Medium	Strength	8.3
ANOVA	15	Zero	Medium	Power	9.1
ANOVA	15	Zero	Medium	Sprint	10.4
ANOVA	15	Zero	Large	Strength	7.3
ANOVA	15	Zero	Large	Power	7.9
ANOVA	15	Zero	Large	Sprint	8
ANOVA	15	Small	Small	Strength	19.8
ANOVA	15	Small	Small	Power	23.4
ANOVA	15	Small	Small	Sprint	28.2
ANOVA	15	Small	Medium	Strength	17.8
ANOVA	15	Small	Medium	Power	19.1
ANOVA	15	Small	Medium	Sprint	21.6
ANOVA	15	Small	Large	Strength	13.3
ANOVA	15	Small	Large	Power	13.3
ANOVA	15	Small	Large	Sprint	13.4
ANOVA	15	Medium	Small	Strength	26.9
ANOVA	15	Medium	Small	Power	30.9
ANOVA	15	Medium	Small	Sprint	37.6
ANOVA	15	Medium	Medium	Strength	23.4
ANOVA	15	Medium	Medium	Power	24.9
ANOVA	15	Medium	Medium	Sprint	27.2
ANOVA	15	Medium	Large	Strength	16.7
ANOVA	15	Medium	Large	Power	16.4
ANOVA	15	Medium	Large	Sprint	15.8
ANOVA	25	Zero	Small	Strength	11.5
ANOVA	25	Zero	Small	Power	14
ANOVA	25	Zero	Small	Sprint	18.1
ANOVA	25	Zero	Medium	Strength	10.3

ANOVA	25	Zero	Medium	Power	12.1
ANOVA	25	Zero	Medium	Sprint	14.4
ANOVA	25	Zero	Large	Strength	8.6
ANOVA	25	Zero	Large	Power	9.2
ANOVA	25	Zero	Large	Sprint	9.7
ANOVA	25	Small	Small	Strength	32.5
ANOVA	25	Small	Small	Power	38.1
ANOVA	25	Small	Small	Sprint	45.6
ANOVA	25	Small	Medium	Strength	28.3
ANOVA	25	Small	Medium	Power	30.9
ANOVA	25	Small	Medium	Sprint	34.5
ANOVA	25	Small	Large	Strength	19.9
ANOVA	25	Small	Large	Power	20.1
ANOVA	25	Small	Large	Sprint	19.6
ANOVA	25	Medium	Small	Strength	48.4
ANOVA	25	Medium	Small	Power	54.6
ANOVA	25	Medium	Small	Sprint	63.7
ANOVA	25	Medium	Medium	Strength	40.7
ANOVA	25	Medium	Medium	Power	43.2
ANOVA	25	Medium	Medium	Sprint	46.3
ANOVA	25	Medium	Large	Strength	27.5
ANOVA	25	Medium	Large	Power	26.4
ANOVA	25	Medium	Large	Sprint	25
ANOVA	50	Zero	Small	Strength	17
ANOVA	50	Zero	Small	Power	21.5
ANOVA	50	Zero	Small	Sprint	30.2
ANOVA	50	Zero	Medium	Strength	15.1
ANOVA	50	Zero	Medium	Power	18.4
ANOVA	50	Zero	Medium	Sprint	22.7
ANOVA	50	Zero	Large	Strength	11.5
ANOVA	50	Zero	Large	Power	12.8
ANOVA	50	Zero	Large	Sprint	14
ANOVA	50	Small	Small	Strength	61
ANOVA	50	Small	Small	Power	68.5
ANOVA	50	Small	Small	Sprint	77.5
ANOVA	50	Small	Medium	Strength	53.1
ANOVA	50	Small	Medium	Power	57.6
ANOVA	50	Small	Medium	Sprint	62
ANOVA	50	Small	Large	Strength	36.5
ANOVA	50	Small	Large	Power	36.3
ANOVA	50	Small	Large	Sprint	34.7
ANOVA	50	Medium	Small	Strength	84.6
ANOVA	50	Medium	Small	Power	89.3
ANOVA	50	Medium	Small	Sprint	94.2
ANOVA	50	Medium	Medium	Strength	75.5
ANOVA	50	Medium	Medium	Power	78.1
ANOVA	50	Medium	Medium	Sprint	80
ANOVA	50	Medium	Large	Strength	52.6
ANOVA	50	Medium	Large	Power	50
ANOVA	50	Medium	Large	Sprint	46.9

T-Test	10	Zero	Small	Strength	2
T-Test	10	Zero	Small	Power	1.6
T-Test	10	Zero	Small	Sprint	1.3
T-Test	10	Zero	Medium	Strength	2.1
T-Test	10	Zero	Medium	Power	1.8
T-Test	10	Zero	Medium	Sprint	1.5
T-Test	10	Zero	Large	Strength	2.5
T-Test	10	Zero	Large	Power	2.2
T-Test	10	Zero	Large	Sprint	2
T-Test	10	Small	Small	Strength	2.2
T-Test	10	Small	Small	Power	1.6
T-Test	10	Small	Small	Sprint	1.2
T-Test	10	Small	Medium	Strength	2.3
T-Test	10	Small	Medium	Power	1.8
T-Test	10	Small	Medium	Sprint	1.4
T-Test	10	Small	Large	Strength	2.8
T-Test	10	Small	Large	Power	2.3
T-Test	10	Small	Large	Sprint	2.1
T-Test	10	Medium	Small	Strength	1.6
T-Test	10	Medium	Small	Power	1.1
T-Test	10	Medium	Small	Sprint	0.8
T-Test	10	Medium	Medium	Strength	2
T-Test	10	Medium	Medium	Power	1.4
T-Test	10	Medium	Medium	Sprint	1
T-Test	10	Medium	Large	Strength	2.7
T-Test	10	Medium	Large	Power	2.1
T-Test	10	Medium	Large	Sprint	1.8
T-Test	15	Zero	Small	Strength	2.9
T-Test	15	Zero	Small	Power	2.5
T-Test	15	Zero	Small	Sprint	1.6
T-Test	15	Zero	Medium	Strength	3.2
T-Test	15	Zero	Medium	Power	2.6
T-Test	15	Zero	Medium	Sprint	2
T-Test	15	Zero	Large	Strength	3.5
T-Test	15	Zero	Large	Power	3.1
T-Test	15	Zero	Large	Sprint	2.8
T-Test	15	Small	Small	Strength	2.6
T-Test	15	Small	Small	Power	1.9
T-Test	15	Small	Small	Sprint	1.5
T-Test	15	Small	Medium	Strength	2.7
T-Test	15	Small	Medium	Power	2.3
T-Test	15	Small	Medium	Sprint	1.9
T-Test	15	Small	Large	Strength	3.1
T-Test	15	Small	Large	Power	2.8
T-Test	15	Small	Large	Sprint	2.6
T-Test	15	Medium	Small	Strength	1.8
T-Test	15	Medium	Small	Power	1.3
T-Test	15	Medium	Small	Sprint	0.8
T-Test	15	Medium	Medium	Strength	2
T-Test	15	Medium	Medium	Power	1.7

T-Test	15	Medium	Medium	Sprint	1.2
T-Test	15	Medium	Large	Strength	2.8
T-Test	15	Medium	Large	Power	2.4
T-Test	15	Medium	Large	Sprint	2.1
T-Test	25	Zero	Small	Strength	6
T-Test	25	Zero	Small	Power	5.3
T-Test	25	Zero	Small	Sprint	4
T-Test	25	Zero	Medium	Strength	6.1
T-Test	25	Zero	Medium	Power	5.3
T-Test	25	Zero	Medium	Sprint	4.4
T-Test	25	Zero	Large	Strength	6.3
T-Test	25	Zero	Large	Power	6
T-Test	25	Zero	Large	Sprint	5.6
T-Test	25	Small	Small	Strength	3.6
T-Test	25	Small	Small	Power	3.4
T-Test	25	Small	Small	Sprint	2.9
T-Test	25	Small	Medium	Strength	3.7
T-Test	25	Small	Medium	Power	3.6
T-Test	25	Small	Medium	Sprint	3.4
T-Test	25	Small	Large	Strength	3.9
T-Test	25	Small	Large	Power	4.2
T-Test	25	Small	Large	Sprint	4.3
T-Test	25	Medium	Small	Strength	2.2
T-Test	25	Medium	Small	Power	2.1
T-Test	25	Medium	Small	Sprint	1.6
T-Test	25	Medium	Medium	Strength	2.4
T-Test	25	Medium	Medium	Power	2.4
T-Test	25	Medium	Medium	Sprint	2.2
T-Test	25	Medium	Large	Strength	3.2
T-Test	25	Medium	Large	Power	3.3
T-Test	25	Medium	Large	Sprint	3.3
T-Test	50	Zero	Small	Strength	17.8
T-Test	50	Zero	Small	Power	18.6
T-Test	50	Zero	Small	Sprint	19.7
T-Test	50	Zero	Medium	Strength	17.3
T-Test	50	Zero	Medium	Power	18.1
T-Test	50	Zero	Medium	Sprint	19.4
T-Test	50	Zero	Large	Strength	16
T-Test	50	Zero	Large	Power	17.1
T-Test	50	Zero	Large	Sprint	17.9
T-Test	50	Small	Small	Strength	7.4
T-Test	50	Small	Small	Power	8.7
T-Test	50	Small	Small	Sprint	10.5
T-Test	50	Small	Medium	Strength	7.4
T-Test	50	Small	Medium	Power	8.8
T-Test	50	Small	Medium	Sprint	10.5
T-Test	50	Small	Large	Strength	7
T-Test	50	Small	Large	Power	8.8
T-Test	50	Small	Large	Sprint	10.6
T-Test	50	Medium	Small	Strength	3.5

T-Test	50	Medium	Small	Power	4.9
T-Test	50	Medium	Small	Sprint	6
T-Test	50	Medium	Medium	Strength	3.8
T-Test	50	Medium	Medium	Power	5.2
T-Test	50	Medium	Medium	Sprint	6.8
T-Test	50	Medium	Large	Strength	4.2
T-Test	50	Medium	Large	Power	5.8
T-Test	50	Medium	Large	Sprint	7.4

Medium ATE and Zero Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	13.3
ANCOVA	10	Zero	Small	Power	15.9
ANCOVA	10	Zero	Small	Sprint	21.8
ANCOVA	10	Zero	Medium	Strength	12
ANCOVA	10	Zero	Medium	Power	13.8
ANCOVA	10	Zero	Medium	Sprint	17.1
ANCOVA	10	Zero	Large	Strength	9.5
ANCOVA	10	Zero	Large	Power	10.3
ANCOVA	10	Zero	Large	Sprint	11.3
ANCOVA	10	Small	Small	Strength	16
ANCOVA	10	Small	Small	Power	19.8
ANCOVA	10	Small	Small	Sprint	27.6
ANCOVA	10	Small	Medium	Strength	14.4
ANCOVA	10	Small	Medium	Power	17
ANCOVA	10	Small	Medium	Sprint	21.1
ANCOVA	10	Small	Large	Strength	11.2
ANCOVA	10	Small	Large	Power	12.1
ANCOVA	10	Small	Large	Sprint	13.2
ANCOVA	10	Medium	Small	Strength	21.5
ANCOVA	10	Medium	Small	Power	26.9
ANCOVA	10	Medium	Small	Sprint	37.8
ANCOVA	10	Medium	Medium	Strength	18.4
ANCOVA	10	Medium	Medium	Power	21.6
ANCOVA	10	Medium	Medium	Sprint	26.7
ANCOVA	10	Medium	Large	Strength	13.2
ANCOVA	10	Medium	Large	Power	14
ANCOVA	10	Medium	Large	Sprint	15
ANCOVA	15	Zero	Small	Strength	18.1
ANCOVA	15	Zero	Small	Power	22.7
ANCOVA	15	Zero	Small	Sprint	32.6
ANCOVA	15	Zero	Medium	Strength	15.9
ANCOVA	15	Zero	Medium	Power	19.2
ANCOVA	15	Zero	Medium	Sprint	24.7
ANCOVA	15	Zero	Large	Strength	12.5
ANCOVA	15	Zero	Large	Power	13.6
ANCOVA	15	Zero	Large	Sprint	15.4
ANCOVA	15	Small	Small	Strength	22.5
ANCOVA	15	Small	Small	Power	29
ANCOVA	15	Small	Small	Sprint	40.9
ANCOVA	15	Small	Medium	Strength	20.1

ANCOVA	15	Small	Medium	Power	24.4
ANCOVA	15	Small	Medium	Sprint	31
ANCOVA	15	Small	Large	Strength	15.1
ANCOVA	15	Small	Large	Power	16.6
ANCOVA	15	Small	Large	Sprint	18.1
ANCOVA	15	Medium	Small	Strength	30.9
ANCOVA	15	Medium	Small	Power	40.4
ANCOVA	15	Medium	Small	Sprint	55.8
ANCOVA	15	Medium	Medium	Strength	26.1
ANCOVA	15	Medium	Medium	Power	31.9
ANCOVA	15	Medium	Medium	Sprint	39.8
ANCOVA	15	Medium	Large	Strength	18
ANCOVA	15	Medium	Large	Power	19.8
ANCOVA	15	Medium	Large	Sprint	21.2
ANCOVA	25	Zero	Small	Strength	28.1
ANCOVA	25	Zero	Small	Power	36.8
ANCOVA	25	Zero	Small	Sprint	51.6
ANCOVA	25	Zero	Medium	Strength	24.6
ANCOVA	25	Zero	Medium	Power	30.5
ANCOVA	25	Zero	Medium	Sprint	40.1
ANCOVA	25	Zero	Large	Strength	18.4
ANCOVA	25	Zero	Large	Power	20.7
ANCOVA	25	Zero	Large	Sprint	23.6
ANCOVA	25	Small	Small	Strength	35.7
ANCOVA	25	Small	Small	Power	46.5
ANCOVA	25	Small	Small	Sprint	63.5
ANCOVA	25	Small	Medium	Strength	31.7
ANCOVA	25	Small	Medium	Power	39
ANCOVA	25	Small	Medium	Sprint	49.4
ANCOVA	25	Small	Large	Strength	22.8
ANCOVA	25	Small	Large	Power	25.4
ANCOVA	25	Small	Large	Sprint	28.5
ANCOVA	25	Medium	Small	Strength	48.7
ANCOVA	25	Medium	Small	Power	62.3
ANCOVA	25	Medium	Small	Sprint	79.2
ANCOVA	25	Medium	Medium	Strength	41.6
ANCOVA	25	Medium	Medium	Power	50.5
ANCOVA	25	Medium	Medium	Sprint	61.7
ANCOVA	25	Medium	Large	Strength	27.9
ANCOVA	25	Medium	Large	Power	30.8
ANCOVA	25	Medium	Large	Sprint	33.6
ANCOVA	50	Zero	Small	Strength	49.2
ANCOVA	50	Zero	Small	Power	63.8
ANCOVA	50	Zero	Small	Sprint	81.2
ANCOVA	50	Zero	Medium	Strength	43.2
ANCOVA	50	Zero	Medium	Power	54.2
ANCOVA	50	Zero	Medium	Sprint	67.9
ANCOVA	50	Zero	Large	Strength	31.7
ANCOVA	50	Zero	Large	Power	36.6
ANCOVA	50	Zero	Large	Sprint	42.4

ANCOVA	50	Small	Small	Strength	61.3
ANCOVA	50	Small	Small	Power	75.9
ANCOVA	50	Small	Small	Sprint	90.5
ANCOVA	50	Small	Medium	Strength	54.9
ANCOVA	50	Small	Medium	Power	66.8
ANCOVA	50	Small	Medium	Sprint	79.1
ANCOVA	50	Small	Large	Strength	40.1
ANCOVA	50	Small	Large	Power	46.1
ANCOVA	50	Small	Large	Sprint	51.3
ANCOVA	50	Medium	Small	Strength	77.8
ANCOVA	50	Medium	Small	Power	89.9
ANCOVA	50	Medium	Small	Sprint	97.8
ANCOVA	50	Medium	Medium	Strength	69.7
ANCOVA	50	Medium	Medium	Power	80.3
ANCOVA	50	Medium	Medium	Sprint	89.5
ANCOVA	50	Medium	Large	Strength	49.5
ANCOVA	50	Medium	Large	Power	54.6
ANCOVA	50	Medium	Large	Sprint	59.1
ANOVA	10	Zero	Small	Strength	15.1
ANOVA	10	Zero	Small	Power	18.3
ANOVA	10	Zero	Small	Sprint	24.7
ANOVA	10	Zero	Medium	Strength	13.8
ANOVA	10	Zero	Medium	Power	15.6
ANOVA	10	Zero	Medium	Sprint	19.7
ANOVA	10	Zero	Large	Strength	11
ANOVA	10	Zero	Large	Power	11.4
ANOVA	10	Zero	Large	Sprint	12.7
ANOVA	10	Small	Small	Strength	14.7
ANOVA	10	Small	Small	Power	17.9
ANOVA	10	Small	Small	Sprint	25
ANOVA	10	Small	Medium	Strength	13.4
ANOVA	10	Small	Medium	Power	15.7
ANOVA	10	Small	Medium	Sprint	20
ANOVA	10	Small	Large	Strength	10.6
ANOVA	10	Small	Large	Power	11.4
ANOVA	10	Small	Large	Sprint	12.6
ANOVA	10	Medium	Small	Strength	14.6
ANOVA	10	Medium	Small	Power	18.1
ANOVA	10	Medium	Small	Sprint	25.5
ANOVA	10	Medium	Medium	Strength	13.3
ANOVA	10	Medium	Medium	Power	15.6
ANOVA	10	Medium	Medium	Sprint	19.9
ANOVA	10	Medium	Large	Strength	10.7
ANOVA	10	Medium	Large	Power	11.5
ANOVA	10	Medium	Large	Sprint	12.6
ANOVA	15	Zero	Small	Strength	19.7
ANOVA	15	Zero	Small	Power	24.8
ANOVA	15	Zero	Small	Sprint	35
ANOVA	15	Zero	Medium	Strength	17.5
ANOVA	15	Zero	Medium	Power	20.9

ANOVA	15	Zero	Medium	Sprint	26.9
ANOVA	15	Zero	Large	Strength	13.2
ANOVA	15	Zero	Large	Power	14.4
ANOVA	15	Zero	Large	Sprint	16.1
ANOVA	15	Small	Small	Strength	19.4
ANOVA	15	Small	Small	Power	24.9
ANOVA	15	Small	Small	Sprint	35.4
ANOVA	15	Small	Medium	Strength	17.1
ANOVA	15	Small	Medium	Power	20.6
ANOVA	15	Small	Medium	Sprint	27.2
ANOVA	15	Small	Large	Strength	12.8
ANOVA	15	Small	Large	Power	14.1
ANOVA	15	Small	Large	Sprint	16
ANOVA	15	Medium	Small	Strength	19.1
ANOVA	15	Medium	Small	Power	24.8
ANOVA	15	Medium	Small	Sprint	35.2
ANOVA	15	Medium	Medium	Strength	17.1
ANOVA	15	Medium	Medium	Power	20.7
ANOVA	15	Medium	Medium	Sprint	26.8
ANOVA	15	Medium	Large	Strength	13
ANOVA	15	Medium	Large	Power	14.3
ANOVA	15	Medium	Large	Sprint	16.3
ANOVA	25	Zero	Small	Strength	29.3
ANOVA	25	Zero	Small	Power	38.4
ANOVA	25	Zero	Small	Sprint	53.3
ANOVA	25	Zero	Medium	Strength	25.8
ANOVA	25	Zero	Medium	Power	32.2
ANOVA	25	Zero	Medium	Sprint	41
ANOVA	25	Zero	Large	Strength	18.4
ANOVA	25	Zero	Large	Power	20.8
ANOVA	25	Zero	Large	Sprint	23.6
ANOVA	25	Small	Small	Strength	28.9
ANOVA	25	Small	Small	Power	38.5
ANOVA	25	Small	Small	Sprint	53
ANOVA	25	Small	Medium	Strength	25.5
ANOVA	25	Small	Medium	Power	31.8
ANOVA	25	Small	Medium	Sprint	41.2
ANOVA	25	Small	Large	Strength	18.3
ANOVA	25	Small	Large	Power	20.3
ANOVA	25	Small	Large	Sprint	23.4
ANOVA	25	Medium	Small	Strength	28.8
ANOVA	25	Medium	Small	Power	38.2
ANOVA	25	Medium	Small	Sprint	53
ANOVA	25	Medium	Medium	Strength	25.3
ANOVA	25	Medium	Medium	Power	31.7
ANOVA	25	Medium	Medium	Sprint	41
ANOVA	25	Medium	Large	Strength	18.1
ANOVA	25	Medium	Large	Power	20.7
ANOVA	25	Medium	Large	Sprint	23.4
ANOVA	50	Zero	Small	Strength	50

ANOVA	50	Zero	Small	Power	64.6
ANOVA	50	Zero	Small	Sprint	81.9
ANOVA	50	Zero	Medium	Strength	43.9
ANOVA	50	Zero	Medium	Power	55
ANOVA	50	Zero	Medium	Sprint	68.3
ANOVA	50	Zero	Large	Strength	31.1
ANOVA	50	Zero	Large	Power	35.4
ANOVA	50	Zero	Large	Sprint	40.3
ANOVA	50	Small	Small	Strength	49.7
ANOVA	50	Small	Small	Power	64.6
ANOVA	50	Small	Small	Sprint	82
ANOVA	50	Small	Medium	Strength	43.8
ANOVA	50	Small	Medium	Power	54.8
ANOVA	50	Small	Medium	Sprint	68.4
ANOVA	50	Small	Large	Strength	30.8
ANOVA	50	Small	Large	Power	35.3
ANOVA	50	Small	Large	Sprint	40.6
ANOVA	50	Medium	Small	Strength	49.4
ANOVA	50	Medium	Small	Power	64.6
ANOVA	50	Medium	Small	Sprint	81.7
ANOVA	50	Medium	Medium	Strength	43.7
ANOVA	50	Medium	Medium	Power	54.8
ANOVA	50	Medium	Medium	Sprint	68
ANOVA	50	Medium	Large	Strength	30.1
ANOVA	50	Medium	Large	Power	35.2
ANOVA	50	Medium	Large	Sprint	40.6
T-Test	10	Zero	Small	Strength	8
T-Test	10	Zero	Small	Power	8.2
T-Test	10	Zero	Small	Sprint	8.6
T-Test	10	Zero	Medium	Strength	7.9
T-Test	10	Zero	Medium	Power	8.3
T-Test	10	Zero	Medium	Sprint	8.4
T-Test	10	Zero	Large	Strength	7.7
T-Test	10	Zero	Large	Power	7.9
T-Test	10	Zero	Large	Sprint	8
T-Test	10	Small	Small	Strength	10.9
T-Test	10	Small	Small	Power	10.9
T-Test	10	Small	Small	Sprint	10.9
T-Test	10	Small	Medium	Strength	10.7
T-Test	10	Small	Medium	Power	10.6
T-Test	10	Small	Medium	Sprint	10.5
T-Test	10	Small	Large	Strength	9.6
T-Test	10	Small	Large	Power	9.7
T-Test	10	Small	Large	Sprint	9.5
T-Test	10	Medium	Small	Strength	14.8
T-Test	10	Medium	Small	Power	14.2
T-Test	10	Medium	Small	Sprint	13.4
T-Test	10	Medium	Medium	Strength	13.7
T-Test	10	Medium	Medium	Power	13.4
T-Test	10	Medium	Medium	Sprint	12.7

T-Test	10	Medium	Large	Strength	11.5
T-Test	10	Medium	Large	Power	11.6
T-Test	10	Medium	Large	Sprint	10.8
T-Test	15	Zero	Small	Strength	9.5
T-Test	15	Zero	Small	Power	10.1
T-Test	15	Zero	Small	Sprint	10.5
T-Test	15	Zero	Medium	Strength	9.3
T-Test	15	Zero	Medium	Power	10.1
T-Test	15	Zero	Medium	Sprint	10.2
T-Test	15	Zero	Large	Strength	9
T-Test	15	Zero	Large	Power	9.6
T-Test	15	Zero	Large	Sprint	9.5
T-Test	15	Small	Small	Strength	14.2
T-Test	15	Small	Small	Power	14.5
T-Test	15	Small	Small	Sprint	14.3
T-Test	15	Small	Medium	Strength	13.7
T-Test	15	Small	Medium	Power	14.1
T-Test	15	Small	Medium	Sprint	13.8
T-Test	15	Small	Large	Strength	12.1
T-Test	15	Small	Large	Power	12.3
T-Test	15	Small	Large	Sprint	12
T-Test	15	Medium	Small	Strength	20.2
T-Test	15	Medium	Small	Power	19.5
T-Test	15	Medium	Small	Sprint	18.1
T-Test	15	Medium	Medium	Strength	18.9
T-Test	15	Medium	Medium	Power	18.3
T-Test	15	Medium	Medium	Sprint	17.1
T-Test	15	Medium	Large	Strength	15.1
T-Test	15	Medium	Large	Power	15.1
T-Test	15	Medium	Large	Sprint	14.1
T-Test	25	Zero	Small	Strength	13.5
T-Test	25	Zero	Small	Power	14.3
T-Test	25	Zero	Small	Sprint	15.3
T-Test	25	Zero	Medium	Strength	13.2
T-Test	25	Zero	Medium	Power	14.3
T-Test	25	Zero	Medium	Sprint	14.8
T-Test	25	Zero	Large	Strength	12.3
T-Test	25	Zero	Large	Power	13
T-Test	25	Zero	Large	Sprint	13.6
T-Test	25	Small	Small	Strength	21.6
T-Test	25	Small	Small	Power	22.2
T-Test	25	Small	Small	Sprint	22.3
T-Test	25	Small	Medium	Strength	20.7
T-Test	25	Small	Medium	Power	21.1
T-Test	25	Small	Medium	Sprint	21.2
T-Test	25	Small	Large	Strength	17.9
T-Test	25	Small	Large	Power	18.1
T-Test	25	Small	Large	Sprint	18
T-Test	25	Medium	Small	Strength	31.8
T-Test	25	Medium	Small	Power	30.6

T-Test	25	Medium	Small	Sprint	28.9
T-Test	25	Medium	Medium	Strength	29.3
T-Test	25	Medium	Medium	Power	28.2
T-Test	25	Medium	Medium	Sprint	27
T-Test	25	Medium	Large	Strength	23
T-Test	25	Medium	Large	Power	22.5
T-Test	25	Medium	Large	Sprint	21.6
T-Test	50	Zero	Small	Strength	22.3
T-Test	50	Zero	Small	Power	24.2
T-Test	50	Zero	Small	Sprint	26.3
T-Test	50	Zero	Medium	Strength	21.8
T-Test	50	Zero	Medium	Power	23.5
T-Test	50	Zero	Medium	Sprint	25.6
T-Test	50	Zero	Large	Strength	20.1
T-Test	50	Zero	Large	Power	21.5
T-Test	50	Zero	Large	Sprint	22.8
T-Test	50	Small	Small	Strength	37.7
T-Test	50	Small	Small	Power	39.4
T-Test	50	Small	Small	Sprint	40
T-Test	50	Small	Medium	Strength	35.8
T-Test	50	Small	Medium	Power	37.4
T-Test	50	Small	Medium	Sprint	37.7
T-Test	50	Small	Large	Strength	30.6
T-Test	50	Small	Large	Power	31.6
T-Test	50	Small	Large	Sprint	32
T-Test	50	Medium	Small	Strength	54.9
T-Test	50	Medium	Small	Power	54.4
T-Test	50	Medium	Small	Sprint	51.3
T-Test	50	Medium	Medium	Strength	51
T-Test	50	Medium	Medium	Power	50.6
T-Test	50	Medium	Medium	Sprint	47.9
T-Test	50	Medium	Large	Strength	40.8
T-Test	50	Medium	Large	Power	40.3
T-Test	50	Medium	Large	Sprint	38.9

Medium ATE and Positive Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	13.2
ANCOVA	10	Zero	Small	Power	16.1
ANCOVA	10	Zero	Small	Sprint	22
ANCOVA	10	Zero	Medium	Strength	13.4
ANCOVA	10	Zero	Medium	Power	15.5
ANCOVA	10	Zero	Medium	Sprint	19.9
ANCOVA	10	Zero	Large	Strength	13.5
ANCOVA	10	Zero	Large	Power	14.8
ANCOVA	10	Zero	Large	Sprint	16.6
ANCOVA	10	Small	Small	Strength	15.9
ANCOVA	10	Small	Small	Power	19.9
ANCOVA	10	Small	Small	Sprint	27.7
ANCOVA	10	Small	Medium	Strength	15.5
ANCOVA	10	Small	Medium	Power	18.6

ANCOVA	10	Small	Medium	Sprint	23.5
ANCOVA	10	Small	Large	Strength	14.5
ANCOVA	10	Small	Large	Power	16.1
ANCOVA	10	Small	Large	Sprint	18.2
ANCOVA	10	Medium	Small	Strength	21
ANCOVA	10	Medium	Small	Power	26.9
ANCOVA	10	Medium	Small	Sprint	37.6
ANCOVA	10	Medium	Medium	Strength	19.5
ANCOVA	10	Medium	Medium	Power	23.5
ANCOVA	10	Medium	Medium	Sprint	29.5
ANCOVA	10	Medium	Large	Strength	16
ANCOVA	10	Medium	Large	Power	18.2
ANCOVA	10	Medium	Large	Sprint	20.5
ANCOVA	15	Zero	Small	Strength	17.8
ANCOVA	15	Zero	Small	Power	22.7
ANCOVA	15	Zero	Small	Sprint	32.3
ANCOVA	15	Zero	Medium	Strength	18.2
ANCOVA	15	Zero	Medium	Power	21.8
ANCOVA	15	Zero	Medium	Sprint	29
ANCOVA	15	Zero	Large	Strength	18
ANCOVA	15	Zero	Large	Power	20.4
ANCOVA	15	Zero	Large	Sprint	23.8
ANCOVA	15	Small	Small	Strength	22
ANCOVA	15	Small	Small	Power	28.4
ANCOVA	15	Small	Small	Sprint	40.6
ANCOVA	15	Small	Medium	Strength	21.2
ANCOVA	15	Small	Medium	Power	26.4
ANCOVA	15	Small	Medium	Sprint	34.6
ANCOVA	15	Small	Large	Strength	19.6
ANCOVA	15	Small	Large	Power	22.5
ANCOVA	15	Small	Large	Sprint	25.9
ANCOVA	15	Medium	Small	Strength	30.1
ANCOVA	15	Medium	Small	Power	39.5
ANCOVA	15	Medium	Small	Sprint	54.7
ANCOVA	15	Medium	Medium	Strength	27.6
ANCOVA	15	Medium	Medium	Power	34.1
ANCOVA	15	Medium	Medium	Sprint	42.9
ANCOVA	15	Medium	Large	Strength	21.9
ANCOVA	15	Medium	Large	Power	25.5
ANCOVA	15	Medium	Large	Sprint	29.4
ANCOVA	25	Zero	Small	Strength	27.7
ANCOVA	25	Zero	Small	Power	36.7
ANCOVA	25	Zero	Small	Sprint	51.1
ANCOVA	25	Zero	Medium	Strength	27.8
ANCOVA	25	Zero	Medium	Power	35
ANCOVA	25	Zero	Medium	Sprint	45.1
ANCOVA	25	Zero	Large	Strength	27.5
ANCOVA	25	Zero	Large	Power	32.1
ANCOVA	25	Zero	Large	Sprint	37
ANCOVA	25	Small	Small	Strength	34.8

ANCOVA	25	Small	Small	Power	45.9
ANCOVA	25	Small	Small	Sprint	62.4
ANCOVA	25	Small	Medium	Strength	33.4
ANCOVA	25	Small	Medium	Power	42.2
ANCOVA	25	Small	Medium	Sprint	53.7
ANCOVA	25	Small	Large	Strength	30.2
ANCOVA	25	Small	Large	Power	35.1
ANCOVA	25	Small	Large	Sprint	40.8
ANCOVA	25	Medium	Small	Strength	47.6
ANCOVA	25	Medium	Small	Power	61.1
ANCOVA	25	Medium	Small	Sprint	78
ANCOVA	25	Medium	Medium	Strength	43.3
ANCOVA	25	Medium	Medium	Power	53.6
ANCOVA	25	Medium	Medium	Sprint	65
ANCOVA	25	Medium	Large	Strength	34.3
ANCOVA	25	Medium	Large	Power	40.1
ANCOVA	25	Medium	Large	Sprint	45.4
ANCOVA	50	Zero	Small	Strength	48.4
ANCOVA	50	Zero	Small	Power	62.7
ANCOVA	50	Zero	Small	Sprint	80.2
ANCOVA	50	Zero	Medium	Strength	48.6
ANCOVA	50	Zero	Medium	Power	60.4
ANCOVA	50	Zero	Medium	Sprint	74.2
ANCOVA	50	Zero	Large	Strength	48.7
ANCOVA	50	Zero	Large	Power	56.2
ANCOVA	50	Zero	Large	Sprint	64.1
ANCOVA	50	Small	Small	Strength	59.4
ANCOVA	50	Small	Small	Power	75
ANCOVA	50	Small	Small	Sprint	89.7
ANCOVA	50	Small	Medium	Strength	57.5
ANCOVA	50	Small	Medium	Power	70.4
ANCOVA	50	Small	Medium	Sprint	82.8
ANCOVA	50	Small	Large	Strength	53
ANCOVA	50	Small	Large	Power	61.3
ANCOVA	50	Small	Large	Sprint	68.9
ANCOVA	50	Medium	Small	Strength	76.3
ANCOVA	50	Medium	Small	Power	89
ANCOVA	50	Medium	Small	Sprint	97.3
ANCOVA	50	Medium	Medium	Strength	71.3
ANCOVA	50	Medium	Medium	Power	82.4
ANCOVA	50	Medium	Medium	Sprint	91.5
ANCOVA	50	Medium	Large	Strength	60.1
ANCOVA	50	Medium	Large	Power	67.8
ANCOVA	50	Medium	Large	Sprint	74.4
ANOVA	10	Zero	Small	Strength	15.1
ANOVA	10	Zero	Small	Power	18.3
ANOVA	10	Zero	Small	Sprint	24.9
ANOVA	10	Zero	Medium	Strength	13.6
ANOVA	10	Zero	Medium	Power	15.6
ANOVA	10	Zero	Medium	Sprint	19.5

ANOVA	10	Zero	Large	Strength	10.7
ANOVA	10	Zero	Large	Power	11.6
ANOVA	10	Zero	Large	Sprint	12.7
ANOVA	10	Small	Small	Strength	4.5
ANOVA	10	Small	Small	Power	5.8
ANOVA	10	Small	Small	Sprint	9.3
ANOVA	10	Small	Medium	Strength	4.6
ANOVA	10	Small	Medium	Power	5.8
ANOVA	10	Small	Medium	Sprint	8.4
ANOVA	10	Small	Large	Strength	5.1
ANOVA	10	Small	Large	Power	5.9
ANOVA	10	Small	Large	Sprint	7
ANOVA	10	Medium	Small	Strength	1.3
ANOVA	10	Medium	Small	Power	1.9
ANOVA	10	Medium	Small	Sprint	3.7
ANOVA	10	Medium	Medium	Strength	1.8
ANOVA	10	Medium	Medium	Power	2.6
ANOVA	10	Medium	Medium	Sprint	4.3
ANOVA	10	Medium	Large	Strength	3
ANOVA	10	Medium	Large	Power	3.8
ANOVA	10	Medium	Large	Sprint	5
ANOVA	15	Zero	Small	Strength	19.9
ANOVA	15	Zero	Small	Power	24.7
ANOVA	15	Zero	Small	Sprint	35.1
ANOVA	15	Zero	Medium	Strength	17.3
ANOVA	15	Zero	Medium	Power	20.8
ANOVA	15	Zero	Medium	Sprint	26.6
ANOVA	15	Zero	Large	Strength	12.9
ANOVA	15	Zero	Large	Power	14.5
ANOVA	15	Zero	Large	Sprint	16.3
ANOVA	15	Small	Small	Strength	4.6
ANOVA	15	Small	Small	Power	6.8
ANOVA	15	Small	Small	Sprint	12.2
ANOVA	15	Small	Medium	Strength	4.7
ANOVA	15	Small	Medium	Power	6.7
ANOVA	15	Small	Medium	Sprint	10.5
ANOVA	15	Small	Large	Strength	5
ANOVA	15	Small	Large	Power	6.1
ANOVA	15	Small	Large	Sprint	7.9
ANOVA	15	Medium	Small	Strength	1.1
ANOVA	15	Medium	Small	Power	1.9
ANOVA	15	Medium	Small	Sprint	4.4
ANOVA	15	Medium	Medium	Strength	1.7
ANOVA	15	Medium	Medium	Power	2.5
ANOVA	15	Medium	Medium	Sprint	5
ANOVA	15	Medium	Large	Strength	2.8
ANOVA	15	Medium	Large	Power	3.7
ANOVA	15	Medium	Large	Sprint	5.1
ANOVA	25	Zero	Small	Strength	29.4
ANOVA	25	Zero	Small	Power	38.4

ANOVA	25	Zero	Small	Sprint	53.4
ANOVA	25	Zero	Medium	Strength	25.6
ANOVA	25	Zero	Medium	Power	31.7
ANOVA	25	Zero	Medium	Sprint	41.3
ANOVA	25	Zero	Large	Strength	18.3
ANOVA	25	Zero	Large	Power	20.9
ANOVA	25	Zero	Large	Sprint	23.5
ANOVA	25	Small	Small	Strength	5.9
ANOVA	25	Small	Small	Power	9.9
ANOVA	25	Small	Small	Sprint	19.6
ANOVA	25	Small	Medium	Strength	5.6
ANOVA	25	Small	Medium	Power	9
ANOVA	25	Small	Medium	Sprint	15.5
ANOVA	25	Small	Large	Strength	5.5
ANOVA	25	Small	Large	Power	7.6
ANOVA	25	Small	Large	Sprint	10.1
ANOVA	25	Medium	Small	Strength	1
ANOVA	25	Medium	Small	Power	2.4
ANOVA	25	Medium	Small	Sprint	7.1
ANOVA	25	Medium	Medium	Strength	1.6
ANOVA	25	Medium	Medium	Power	2.8
ANOVA	25	Medium	Medium	Sprint	7
ANOVA	25	Medium	Large	Strength	2.7
ANOVA	25	Medium	Large	Power	3.8
ANOVA	25	Medium	Large	Sprint	6
ANOVA	50	Zero	Small	Strength	50.1
ANOVA	50	Zero	Small	Power	64.7
ANOVA	50	Zero	Small	Sprint	81.9
ANOVA	50	Zero	Medium	Strength	43.9
ANOVA	50	Zero	Medium	Power	55.1
ANOVA	50	Zero	Medium	Sprint	68.4
ANOVA	50	Zero	Large	Strength	30.6
ANOVA	50	Zero	Large	Power	35.7
ANOVA	50	Zero	Large	Sprint	40.5
ANOVA	50	Small	Small	Strength	8.6
ANOVA	50	Small	Small	Power	17.1
ANOVA	50	Small	Small	Sprint	37.4
ANOVA	50	Small	Medium	Strength	8
ANOVA	50	Small	Medium	Power	14.7
ANOVA	50	Small	Medium	Sprint	27.8
ANOVA	50	Small	Large	Strength	7
ANOVA	50	Small	Large	Power	10.7
ANOVA	50	Small	Large	Sprint	16.1
ANOVA	50	Medium	Small	Strength	1.2
ANOVA	50	Medium	Small	Power	3.6
ANOVA	50	Medium	Small	Sprint	14.7
ANOVA	50	Medium	Medium	Strength	1.5
ANOVA	50	Medium	Medium	Power	4
ANOVA	50	Medium	Medium	Sprint	12.2
ANOVA	50	Medium	Large	Strength	2.7

ANOVA	50	Medium	Large	Power	4.6
ANOVA	50	Medium	Large	Sprint	8.8
T-Test	10	Zero	Small	Strength	19.8
T-Test	10	Zero	Small	Power	21.1
T-Test	10	Zero	Small	Sprint	24
T-Test	10	Zero	Medium	Strength	19.1
T-Test	10	Zero	Medium	Power	20.7
T-Test	10	Zero	Medium	Sprint	22.8
T-Test	10	Zero	Large	Strength	17.6
T-Test	10	Zero	Large	Power	18.8
T-Test	10	Zero	Large	Sprint	20.1
T-Test	10	Small	Small	Strength	25.4
T-Test	10	Small	Small	Power	28.5
T-Test	10	Small	Small	Sprint	31.6
T-Test	10	Small	Medium	Strength	24
T-Test	10	Small	Medium	Power	26.9
T-Test	10	Small	Medium	Sprint	29
T-Test	10	Small	Large	Strength	20.4
T-Test	10	Small	Large	Power	22.1
T-Test	10	Small	Large	Sprint	23.7
T-Test	10	Medium	Small	Strength	32.5
T-Test	10	Medium	Small	Power	36.7
T-Test	10	Medium	Small	Sprint	39.9
T-Test	10	Medium	Medium	Strength	29.6
T-Test	10	Medium	Medium	Power	32.8
T-Test	10	Medium	Medium	Sprint	35.8
T-Test	10	Medium	Large	Strength	22.9
T-Test	10	Medium	Large	Power	24.9
T-Test	10	Medium	Large	Sprint	26.6
T-Test	15	Zero	Small	Strength	35.1
T-Test	15	Zero	Small	Power	39.4
T-Test	15	Zero	Small	Sprint	46.2
T-Test	15	Zero	Medium	Strength	33.7
T-Test	15	Zero	Medium	Power	37.9
T-Test	15	Zero	Medium	Sprint	43.3
T-Test	15	Zero	Large	Strength	29.6
T-Test	15	Zero	Large	Power	32.9
T-Test	15	Zero	Large	Sprint	36.4
T-Test	15	Small	Small	Strength	41.9
T-Test	15	Small	Small	Power	49.1
T-Test	15	Small	Small	Sprint	57.1
T-Test	15	Small	Medium	Strength	39.3
T-Test	15	Small	Medium	Power	45.7
T-Test	15	Small	Medium	Sprint	52.3
T-Test	15	Small	Large	Strength	32.3
T-Test	15	Small	Large	Power	36.7
T-Test	15	Small	Large	Sprint	40.6
T-Test	15	Medium	Small	Strength	51.6
T-Test	15	Medium	Small	Power	61
T-Test	15	Medium	Small	Sprint	68.1

T-Test	15	Medium	Medium	Strength	46.7
T-Test	15	Medium	Medium	Power	54.6
T-Test	15	Medium	Medium	Sprint	61.1
T-Test	15	Medium	Large	Strength	35.2
T-Test	15	Medium	Large	Power	40.2
T-Test	15	Medium	Large	Sprint	44.4
T-Test	25	Zero	Small	Strength	66.6
T-Test	25	Zero	Small	Power	75.2
T-Test	25	Zero	Small	Sprint	84.7
T-Test	25	Zero	Medium	Strength	63.9
T-Test	25	Zero	Medium	Power	72.1
T-Test	25	Zero	Medium	Sprint	81
T-Test	25	Zero	Large	Strength	56.6
T-Test	25	Zero	Large	Power	62.8
T-Test	25	Zero	Large	Sprint	69.4
T-Test	25	Small	Small	Strength	70.5
T-Test	25	Small	Small	Power	81.1
T-Test	25	Small	Small	Sprint	90.4
T-Test	25	Small	Medium	Strength	66.8
T-Test	25	Small	Medium	Power	77
T-Test	25	Small	Medium	Sprint	86.1
T-Test	25	Small	Large	Strength	55.8
T-Test	25	Small	Large	Power	64.2
T-Test	25	Small	Large	Sprint	71.4
T-Test	25	Medium	Small	Strength	80.1
T-Test	25	Medium	Small	Power	89.9
T-Test	25	Medium	Small	Sprint	95.7
T-Test	25	Medium	Medium	Strength	74.5
T-Test	25	Medium	Medium	Power	84.4
T-Test	25	Medium	Medium	Sprint	91.5
T-Test	25	Medium	Large	Strength	59
T-Test	25	Medium	Large	Power	67.2
T-Test	25	Medium	Large	Sprint	74.8
T-Test	50	Zero	Small	Strength	97.4
T-Test	50	Zero	Small	Power	99.4
T-Test	50	Zero	Small	Sprint	100
T-Test	50	Zero	Medium	Strength	96.6
T-Test	50	Zero	Medium	Power	98.9
T-Test	50	Zero	Medium	Sprint	99.8
T-Test	50	Zero	Large	Strength	92.6
T-Test	50	Zero	Large	Power	96.2
T-Test	50	Zero	Large	Sprint	98.3
T-Test	50	Small	Small	Strength	97.2
T-Test	50	Small	Small	Power	99.5
T-Test	50	Small	Small	Sprint	100
T-Test	50	Small	Medium	Strength	95.6
T-Test	50	Small	Medium	Power	98.9
T-Test	50	Small	Medium	Sprint	99.9
T-Test	50	Small	Large	Strength	89
T-Test	50	Small	Large	Power	94.9

T-Test	50	Small	Large	Sprint	97.8
T-Test	50	Medium	Small	Strength	98.9
T-Test	50	Medium	Small	Power	99.9
T-Test	50	Medium	Small	Sprint	100
T-Test	50	Medium	Medium	Strength	97.7
T-Test	50	Medium	Medium	Power	99.7
T-Test	50	Medium	Medium	Sprint	100
T-Test	50	Medium	Large	Strength	90.3
T-Test	50	Medium	Large	Power	95.8
T-Test	50	Medium	Large	Sprint	98.4

Medium ATE and 50egative Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	12.5
ANCOVA	10	Zero	Small	Power	15.2
ANCOVA	10	Zero	Small	Sprint	20.3
ANCOVA	10	Zero	Medium	Strength	10.1
ANCOVA	10	Zero	Medium	Power	11.3
ANCOVA	10	Zero	Medium	Sprint	13.9
ANCOVA	10	Zero	Large	Strength	6.2
ANCOVA	10	Zero	Large	Power	6.1
ANCOVA	10	Zero	Large	Sprint	6.7
ANCOVA	10	Small	Small	Strength	14.7
ANCOVA	10	Small	Small	Power	19.1
ANCOVA	10	Small	Small	Sprint	26.2
ANCOVA	10	Small	Medium	Strength	12.2
ANCOVA	10	Small	Medium	Power	14.6
ANCOVA	10	Small	Medium	Sprint	17.7
ANCOVA	10	Small	Large	Strength	8.2
ANCOVA	10	Small	Large	Power	8.3
ANCOVA	10	Small	Large	Sprint	8.4
ANCOVA	10	Medium	Small	Strength	20.4
ANCOVA	10	Medium	Small	Power	25.9
ANCOVA	10	Medium	Small	Sprint	35.8
ANCOVA	10	Medium	Medium	Strength	16.2
ANCOVA	10	Medium	Medium	Power	18.9
ANCOVA	10	Medium	Medium	Sprint	23.1
ANCOVA	10	Medium	Large	Strength	10.5
ANCOVA	10	Medium	Large	Power	9.8
ANCOVA	10	Medium	Large	Sprint	10.1
ANCOVA	15	Zero	Small	Strength	17.1
ANCOVA	15	Zero	Small	Power	21.4
ANCOVA	15	Zero	Small	Sprint	30.2
ANCOVA	15	Zero	Medium	Strength	13.3
ANCOVA	15	Zero	Medium	Power	15.8
ANCOVA	15	Zero	Medium	Sprint	19.7
ANCOVA	15	Zero	Large	Strength	7.3
ANCOVA	15	Zero	Large	Power	7.7
ANCOVA	15	Zero	Large	Sprint	8.2
ANCOVA	15	Small	Small	Strength	21
ANCOVA	15	Small	Small	Power	27.5

ANCOVA	15	Small	Small	Sprint	38.7
ANCOVA	15	Small	Medium	Strength	17
ANCOVA	15	Small	Medium	Power	20.8
ANCOVA	15	Small	Medium	Sprint	25.8
ANCOVA	15	Small	Large	Strength	10.4
ANCOVA	15	Small	Large	Power	10.7
ANCOVA	15	Small	Large	Sprint	11
ANCOVA	15	Medium	Small	Strength	29.3
ANCOVA	15	Medium	Small	Power	38.2
ANCOVA	15	Medium	Small	Sprint	52.9
ANCOVA	15	Medium	Medium	Strength	23
ANCOVA	15	Medium	Medium	Power	27.7
ANCOVA	15	Medium	Medium	Sprint	34.1
ANCOVA	15	Medium	Large	Strength	13.4
ANCOVA	15	Medium	Large	Power	13.4
ANCOVA	15	Medium	Large	Sprint	13.4
ANCOVA	25	Zero	Small	Strength	26.5
ANCOVA	25	Zero	Small	Power	34.2
ANCOVA	25	Zero	Small	Sprint	48.2
ANCOVA	25	Zero	Medium	Strength	19.9
ANCOVA	25	Zero	Medium	Power	24.5
ANCOVA	25	Zero	Medium	Sprint	31.7
ANCOVA	25	Zero	Large	Strength	9.8
ANCOVA	25	Zero	Large	Power	10.7
ANCOVA	25	Zero	Large	Sprint	11.8
ANCOVA	25	Small	Small	Strength	32.8
ANCOVA	25	Small	Small	Power	43.8
ANCOVA	25	Small	Small	Sprint	59.7
ANCOVA	25	Small	Medium	Strength	26.3
ANCOVA	25	Small	Medium	Power	33.2
ANCOVA	25	Small	Medium	Sprint	41.6
ANCOVA	25	Small	Large	Strength	15
ANCOVA	25	Small	Large	Power	15.8
ANCOVA	25	Small	Large	Sprint	16.6
ANCOVA	25	Medium	Small	Strength	46.3
ANCOVA	25	Medium	Small	Power	59.3
ANCOVA	25	Medium	Small	Sprint	76.6
ANCOVA	25	Medium	Medium	Strength	36.8
ANCOVA	25	Medium	Medium	Power	44
ANCOVA	25	Medium	Medium	Sprint	53.7
ANCOVA	25	Medium	Large	Strength	20.3
ANCOVA	25	Medium	Large	Power	20.9
ANCOVA	25	Medium	Large	Sprint	20.7
ANCOVA	50	Zero	Small	Strength	45.9
ANCOVA	50	Zero	Small	Power	60.3
ANCOVA	50	Zero	Small	Sprint	77.8
ANCOVA	50	Zero	Medium	Strength	34.7
ANCOVA	50	Zero	Medium	Power	44.4
ANCOVA	50	Zero	Medium	Sprint	56.6
ANCOVA	50	Zero	Large	Strength	15.4

ANCOVA	50	Zero	Large	Power	17.6
ANCOVA	50	Zero	Large	Sprint	20
ANCOVA	50	Small	Small	Strength	58
ANCOVA	50	Small	Small	Power	72.9
ANCOVA	50	Small	Small	Sprint	88.1
ANCOVA	50	Small	Medium	Strength	47.5
ANCOVA	50	Small	Medium	Power	58.4
ANCOVA	50	Small	Medium	Sprint	70.5
ANCOVA	50	Small	Large	Strength	25.9
ANCOVA	50	Small	Large	Power	28
ANCOVA	50	Small	Large	Sprint	30.1
ANCOVA	50	Medium	Small	Strength	75.1
ANCOVA	50	Medium	Small	Power	87.8
ANCOVA	50	Medium	Small	Sprint	96.8
ANCOVA	50	Medium	Medium	Strength	63.3
ANCOVA	50	Medium	Medium	Power	73.7
ANCOVA	50	Medium	Medium	Sprint	83.8
ANCOVA	50	Medium	Large	Strength	35.9
ANCOVA	50	Medium	Large	Power	37.6
ANCOVA	50	Medium	Large	Sprint	38.4
ANOVA	10	Zero	Small	Strength	15.1
ANOVA	10	Zero	Small	Power	18.4
ANOVA	10	Zero	Small	Sprint	24.8
ANOVA	10	Zero	Medium	Strength	13.7
ANOVA	10	Zero	Medium	Power	15.5
ANOVA	10	Zero	Medium	Sprint	19.5
ANOVA	10	Zero	Large	Strength	10.6
ANOVA	10	Zero	Large	Power	11.4
ANOVA	10	Zero	Large	Sprint	12.7
ANOVA	10	Small	Small	Strength	27
ANOVA	10	Small	Small	Power	33.5
ANOVA	10	Small	Small	Sprint	42.7
ANOVA	10	Small	Medium	Strength	23.8
ANOVA	10	Small	Medium	Power	28
ANOVA	10	Small	Medium	Sprint	32.4
ANOVA	10	Small	Large	Strength	17
ANOVA	10	Small	Large	Power	18.4
ANOVA	10	Small	Large	Sprint	18.7
ANOVA	10	Medium	Small	Strength	34.5
ANOVA	10	Medium	Small	Power	41.4
ANOVA	10	Medium	Small	Sprint	52.6
ANOVA	10	Medium	Medium	Strength	29.7
ANOVA	10	Medium	Medium	Power	33
ANOVA	10	Medium	Medium	Sprint	38.7
ANOVA	10	Medium	Large	Strength	20.6
ANOVA	10	Medium	Large	Power	21.1
ANOVA	10	Medium	Large	Sprint	21.8
ANOVA	15	Zero	Small	Strength	19.6
ANOVA	15	Zero	Small	Power	24.8
ANOVA	15	Zero	Small	Sprint	35

ANOVA	15	Zero	Medium	Strength	17.4
ANOVA	15	Zero	Medium	Power	20.7
ANOVA	15	Zero	Medium	Sprint	27.1
ANOVA	15	Zero	Large	Strength	13
ANOVA	15	Zero	Large	Power	14.5
ANOVA	15	Zero	Large	Sprint	15.9
ANOVA	15	Small	Small	Strength	40.3
ANOVA	15	Small	Small	Power	48.8
ANOVA	15	Small	Small	Sprint	60.9
ANOVA	15	Small	Medium	Strength	34.7
ANOVA	15	Small	Medium	Power	40.3
ANOVA	15	Small	Medium	Sprint	46.5
ANOVA	15	Small	Large	Strength	23.7
ANOVA	15	Small	Large	Power	25.3
ANOVA	15	Small	Large	Sprint	26.2
ANOVA	15	Medium	Small	Strength	52.9
ANOVA	15	Medium	Small	Power	62.7
ANOVA	15	Medium	Small	Sprint	75.4
ANOVA	15	Medium	Medium	Strength	44.9
ANOVA	15	Medium	Medium	Power	50.8
ANOVA	15	Medium	Medium	Sprint	57.3
ANOVA	15	Medium	Large	Strength	30
ANOVA	15	Medium	Large	Power	30.7
ANOVA	15	Medium	Large	Sprint	31.3
ANOVA	25	Zero	Small	Strength	29.4
ANOVA	25	Zero	Small	Power	38.3
ANOVA	25	Zero	Small	Sprint	53.4
ANOVA	25	Zero	Medium	Strength	25.9
ANOVA	25	Zero	Medium	Power	31.9
ANOVA	25	Zero	Medium	Sprint	41.3
ANOVA	25	Zero	Large	Strength	18.3
ANOVA	25	Zero	Large	Power	20.7
ANOVA	25	Zero	Large	Sprint	23.1
ANOVA	25	Small	Small	Strength	62.6
ANOVA	25	Small	Small	Power	73.1
ANOVA	25	Small	Small	Sprint	84.8
ANOVA	25	Small	Medium	Strength	54.5
ANOVA	25	Small	Medium	Power	61.8
ANOVA	25	Small	Medium	Sprint	69.8
ANOVA	25	Small	Large	Strength	37.6
ANOVA	25	Small	Large	Power	39.4
ANOVA	25	Small	Large	Sprint	40.2
ANOVA	25	Medium	Small	Strength	80.9
ANOVA	25	Medium	Small	Power	88.7
ANOVA	25	Medium	Small	Sprint	95.3
ANOVA	25	Medium	Medium	Strength	71.5
ANOVA	25	Medium	Medium	Power	77.1
ANOVA	25	Medium	Medium	Sprint	82.4
ANOVA	25	Medium	Large	Strength	49.1
ANOVA	25	Medium	Large	Power	49.2

ANOVA	25	Medium	Large	Sprint	49.3
ANOVA	50	Zero	Small	Strength	50
ANOVA	50	Zero	Small	Power	64.7
ANOVA	50	Zero	Small	Sprint	82
ANOVA	50	Zero	Medium	Strength	43.9
ANOVA	50	Zero	Medium	Power	55.4
ANOVA	50	Zero	Medium	Sprint	68.5
ANOVA	50	Zero	Large	Strength	30.8
ANOVA	50	Zero	Large	Power	35.9
ANOVA	50	Zero	Large	Sprint	40.3
ANOVA	50	Small	Small	Strength	91.6
ANOVA	50	Small	Small	Power	96.4
ANOVA	50	Small	Small	Sprint	99.1
ANOVA	50	Small	Medium	Strength	85.7
ANOVA	50	Small	Medium	Power	90.7
ANOVA	50	Small	Medium	Sprint	94.7
ANOVA	50	Small	Large	Strength	66.5
ANOVA	50	Small	Large	Power	68.4
ANOVA	50	Small	Large	Sprint	69.2
ANOVA	50	Medium	Small	Strength	99.2
ANOVA	50	Medium	Small	Power	99.8
ANOVA	50	Medium	Small	Sprint	100
ANOVA	50	Medium	Medium	Strength	96.6
ANOVA	50	Medium	Medium	Power	98.1
ANOVA	50	Medium	Medium	Sprint	99
ANOVA	50	Medium	Large	Strength	81.2
ANOVA	50	Medium	Large	Power	81.4
ANOVA	50	Medium	Large	Sprint	80
T-Test	10	Zero	Small	Strength	0.8
T-Test	10	Zero	Small	Power	0.4
T-Test	10	Zero	Small	Sprint	0.3
T-Test	10	Zero	Medium	Strength	0.8
T-Test	10	Zero	Medium	Power	0.6
T-Test	10	Zero	Medium	Sprint	0.4
T-Test	10	Zero	Large	Strength	1.1
T-Test	10	Zero	Large	Power	0.9
T-Test	10	Zero	Large	Sprint	0.7
T-Test	10	Small	Small	Strength	1
T-Test	10	Small	Small	Power	0.5
T-Test	10	Small	Small	Sprint	0.2
T-Test	10	Small	Medium	Strength	1.2
T-Test	10	Small	Medium	Power	0.7
T-Test	10	Small	Medium	Sprint	0.3
T-Test	10	Small	Large	Strength	1.7
T-Test	10	Small	Large	Power	1.1
T-Test	10	Small	Large	Sprint	0.7
T-Test	10	Medium	Small	Strength	1.6
T-Test	10	Medium	Small	Power	0.5
T-Test	10	Medium	Small	Sprint	0.1
T-Test	10	Medium	Medium	Strength	1.8

T-Test	10	Medium	Medium	Power	0.6
T-Test	10	Medium	Medium	Sprint	0.3
T-Test	10	Medium	Large	Strength	2.5
T-Test	10	Medium	Large	Power	1.5
T-Test	10	Medium	Large	Sprint	0.9
T-Test	15	Zero	Small	Strength	0.9
T-Test	15	Zero	Small	Power	0.6
T-Test	15	Zero	Small	Sprint	0.3
T-Test	15	Zero	Medium	Strength	1
T-Test	15	Zero	Medium	Power	0.7
T-Test	15	Zero	Medium	Sprint	0.3
T-Test	15	Zero	Large	Strength	1.4
T-Test	15	Zero	Large	Power	1.1
T-Test	15	Zero	Large	Sprint	0.8
T-Test	15	Small	Small	Strength	0.8
T-Test	15	Small	Small	Power	0.4
T-Test	15	Small	Small	Sprint	0.2
T-Test	15	Small	Medium	Strength	1.2
T-Test	15	Small	Medium	Power	0.5
T-Test	15	Small	Medium	Sprint	0.4
T-Test	15	Small	Large	Strength	1.6
T-Test	15	Small	Large	Power	1.1
T-Test	15	Small	Large	Sprint	0.7
T-Test	15	Medium	Small	Strength	1.5
T-Test	15	Medium	Small	Power	0.4
T-Test	15	Medium	Small	Sprint	0.1
T-Test	15	Medium	Medium	Strength	1.8
T-Test	15	Medium	Medium	Power	0.6
T-Test	15	Medium	Medium	Sprint	0.1
T-Test	15	Medium	Large	Strength	2.6
T-Test	15	Medium	Large	Power	1.4
T-Test	15	Medium	Large	Sprint	0.7
T-Test	25	Zero	Small	Strength	1.4
T-Test	25	Zero	Small	Power	0.8
T-Test	25	Zero	Small	Sprint	0.3
T-Test	25	Zero	Medium	Strength	1.5
T-Test	25	Zero	Medium	Power	1
T-Test	25	Zero	Medium	Sprint	0.5
T-Test	25	Zero	Large	Strength	1.9
T-Test	25	Zero	Large	Power	1.4
T-Test	25	Zero	Large	Sprint	1.1
T-Test	25	Small	Small	Strength	0.8
T-Test	25	Small	Small	Power	0.4
T-Test	25	Small	Small	Sprint	0.1
T-Test	25	Small	Medium	Strength	1
T-Test	25	Small	Medium	Power	0.5
T-Test	25	Small	Medium	Sprint	0.2
T-Test	25	Small	Large	Strength	1.5
T-Test	25	Small	Large	Power	1.1
T-Test	25	Small	Large	Sprint	0.7

T-Test	25	Medium	Small	Strength	1.8
T-Test	25	Medium	Small	Power	0.3
T-Test	25	Medium	Small	Sprint	0
T-Test	25	Medium	Medium	Strength	2.1
T-Test	25	Medium	Medium	Power	0.5
T-Test	25	Medium	Medium	Sprint	0.1
T-Test	25	Medium	Large	Strength	2.8
T-Test	25	Medium	Large	Power	1.4
T-Test	25	Medium	Large	Sprint	0.6
T-Test	50	Zero	Small	Strength	2.9
T-Test	50	Zero	Small	Power	2.1
T-Test	50	Zero	Small	Sprint	1.3
T-Test	50	Zero	Medium	Strength	3.1
T-Test	50	Zero	Medium	Power	2.5
T-Test	50	Zero	Medium	Sprint	1.6
T-Test	50	Zero	Large	Strength	3.6
T-Test	50	Zero	Large	Power	3
T-Test	50	Zero	Large	Sprint	2.6
T-Test	50	Small	Small	Strength	0.7
T-Test	50	Small	Small	Power	0.4
T-Test	50	Small	Small	Sprint	0.2
T-Test	50	Small	Medium	Strength	0.9
T-Test	50	Small	Medium	Power	0.6
T-Test	50	Small	Medium	Sprint	0.3
T-Test	50	Small	Large	Strength	1.5
T-Test	50	Small	Large	Power	1.1
T-Test	50	Small	Large	Sprint	1
T-Test	50	Medium	Small	Strength	2.5
T-Test	50	Medium	Small	Power	0.4
T-Test	50	Medium	Small	Sprint	0
T-Test	50	Medium	Medium	Strength	2.8
T-Test	50	Medium	Medium	Power	0.6
T-Test	50	Medium	Medium	Sprint	0.1
T-Test	50	Medium	Large	Strength	3.3
T-Test	50	Medium	Large	Power	1.3
T-Test	50	Medium	Large	Sprint	0.6

Large ATE and Zero Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	28
ANCOVA	10	Zero	Small	Power	36
ANCOVA	10	Zero	Small	Sprint	50.6
ANCOVA	10	Zero	Medium	Strength	24.5
ANCOVA	10	Zero	Medium	Power	29.9
ANCOVA	10	Zero	Medium	Sprint	39
ANCOVA	10	Zero	Large	Strength	18.1
ANCOVA	10	Zero	Large	Power	19.8
ANCOVA	10	Zero	Large	Sprint	23.4
ANCOVA	10	Small	Small	Strength	35.7
ANCOVA	10	Small	Small	Power	45.4
ANCOVA	10	Small	Small	Sprint	62.3

ANCOVA	10	Small	Medium	Strength	30.9
ANCOVA	10	Small	Medium	Power	38
ANCOVA	10	Small	Medium	Sprint	48.6
ANCOVA	10	Small	Large	Strength	22.4
ANCOVA	10	Small	Large	Power	25.4
ANCOVA	10	Small	Large	Sprint	28.3
ANCOVA	10	Medium	Small	Strength	48.5
ANCOVA	10	Medium	Small	Power	61
ANCOVA	10	Medium	Small	Sprint	78.5
ANCOVA	10	Medium	Medium	Strength	41.1
ANCOVA	10	Medium	Medium	Power	49.6
ANCOVA	10	Medium	Medium	Sprint	60.8
ANCOVA	10	Medium	Large	Strength	27.9
ANCOVA	10	Medium	Large	Power	30.2
ANCOVA	10	Medium	Large	Sprint	32.9
ANCOVA	15	Zero	Small	Strength	40.7
ANCOVA	15	Zero	Small	Power	53.1
ANCOVA	15	Zero	Small	Sprint	71.1
ANCOVA	15	Zero	Medium	Strength	35.5
ANCOVA	15	Zero	Medium	Power	44.6
ANCOVA	15	Zero	Medium	Sprint	56.9
ANCOVA	15	Zero	Large	Strength	25.6
ANCOVA	15	Zero	Large	Power	29.2
ANCOVA	15	Zero	Large	Sprint	34.4
ANCOVA	15	Small	Small	Strength	51.3
ANCOVA	15	Small	Small	Power	65.2
ANCOVA	15	Small	Small	Sprint	82.5
ANCOVA	15	Small	Medium	Strength	45
ANCOVA	15	Small	Medium	Power	55.9
ANCOVA	15	Small	Medium	Sprint	68.7
ANCOVA	15	Small	Large	Strength	32.6
ANCOVA	15	Small	Large	Power	37.2
ANCOVA	15	Small	Large	Sprint	41.7
ANCOVA	15	Medium	Small	Strength	66.7
ANCOVA	15	Medium	Small	Power	81.5
ANCOVA	15	Medium	Small	Sprint	93.7
ANCOVA	15	Medium	Medium	Strength	59
ANCOVA	15	Medium	Medium	Power	69.9
ANCOVA	15	Medium	Medium	Sprint	81
ANCOVA	15	Medium	Large	Strength	41
ANCOVA	15	Medium	Large	Power	44.9
ANCOVA	15	Medium	Large	Sprint	48.5
ANCOVA	25	Zero	Small	Strength	62.4
ANCOVA	25	Zero	Small	Power	76.9
ANCOVA	25	Zero	Small	Sprint	91.2
ANCOVA	25	Zero	Medium	Strength	55.5
ANCOVA	25	Zero	Medium	Power	67.5
ANCOVA	25	Zero	Medium	Sprint	80.7
ANCOVA	25	Zero	Large	Strength	40.7
ANCOVA	25	Zero	Large	Power	46.6

ANCOVA	25	Zero	Large	Sprint	54
ANCOVA	25	Small	Small	Strength	74.5
ANCOVA	25	Small	Small	Power	87.4
ANCOVA	25	Small	Small	Sprint	96.9
ANCOVA	25	Small	Medium	Strength	68
ANCOVA	25	Small	Medium	Power	79.7
ANCOVA	25	Small	Medium	Sprint	90
ANCOVA	25	Small	Large	Strength	51.4
ANCOVA	25	Small	Large	Power	57.9
ANCOVA	25	Small	Large	Sprint	64.3
ANCOVA	25	Medium	Small	Strength	88.9
ANCOVA	25	Medium	Small	Power	96.5
ANCOVA	25	Medium	Small	Sprint	99.6
ANCOVA	25	Medium	Medium	Strength	82.3
ANCOVA	25	Medium	Medium	Power	90.6
ANCOVA	25	Medium	Medium	Sprint	96.2
ANCOVA	25	Medium	Large	Strength	62.7
ANCOVA	25	Medium	Large	Power	67.8
ANCOVA	25	Medium	Large	Sprint	72
ANCOVA	50	Zero	Small	Strength	89.8
ANCOVA	50	Zero	Small	Power	97
ANCOVA	50	Zero	Small	Sprint	99.8
ANCOVA	50	Zero	Medium	Strength	84.6
ANCOVA	50	Zero	Medium	Power	93.2
ANCOVA	50	Zero	Medium	Sprint	98.1
ANCOVA	50	Zero	Large	Strength	68.7
ANCOVA	50	Zero	Large	Power	76.6
ANCOVA	50	Zero	Large	Sprint	83.8
ANCOVA	50	Small	Small	Strength	96.4
ANCOVA	50	Small	Small	Power	99.4
ANCOVA	50	Small	Small	Sprint	100
ANCOVA	50	Small	Medium	Strength	93.4
ANCOVA	50	Small	Medium	Power	97.9
ANCOVA	50	Small	Medium	Sprint	99.6
ANCOVA	50	Small	Large	Strength	81.1
ANCOVA	50	Small	Large	Power	87
ANCOVA	50	Small	Large	Sprint	91.3
ANCOVA	50	Medium	Small	Strength	99.5
ANCOVA	50	Medium	Small	Power	100
ANCOVA	50	Medium	Small	Sprint	100
ANCOVA	50	Medium	Medium	Strength	98.5
ANCOVA	50	Medium	Medium	Power	99.7
ANCOVA	50	Medium	Medium	Sprint	100
ANCOVA	50	Medium	Large	Strength	90.3
ANCOVA	50	Medium	Large	Power	93.5
ANCOVA	50	Medium	Large	Sprint	95.4
ANOVA	10	Zero	Small	Strength	31.5
ANOVA	10	Zero	Small	Power	40.5
ANOVA	10	Zero	Small	Sprint	55.5
ANOVA	10	Zero	Medium	Strength	27.4

ANOVA	10	Zero	Medium	Power	33.8
ANOVA	10	Zero	Medium	Sprint	43.7
ANOVA	10	Zero	Large	Strength	19.7
ANOVA	10	Zero	Large	Power	22.1
ANOVA	10	Zero	Large	Sprint	24.9
ANOVA	10	Small	Small	Strength	31.2
ANOVA	10	Small	Small	Power	40.2
ANOVA	10	Small	Small	Sprint	56
ANOVA	10	Small	Medium	Strength	27.3
ANOVA	10	Small	Medium	Power	33.3
ANOVA	10	Small	Medium	Sprint	43.3
ANOVA	10	Small	Large	Strength	19.8
ANOVA	10	Small	Large	Power	22
ANOVA	10	Small	Large	Sprint	25.5
ANOVA	10	Medium	Small	Strength	30.9
ANOVA	10	Medium	Small	Power	40
ANOVA	10	Medium	Small	Sprint	56.2
ANOVA	10	Medium	Medium	Strength	27.2
ANOVA	10	Medium	Medium	Power	33.7
ANOVA	10	Medium	Medium	Sprint	43.8
ANOVA	10	Medium	Large	Strength	19.7
ANOVA	10	Medium	Large	Power	21.7
ANOVA	10	Medium	Large	Sprint	25.5
ANOVA	15	Zero	Small	Strength	43.3
ANOVA	15	Zero	Small	Power	56.2
ANOVA	15	Zero	Small	Sprint	74.1
ANOVA	15	Zero	Medium	Strength	37.7
ANOVA	15	Zero	Medium	Power	47
ANOVA	15	Zero	Medium	Sprint	60.1
ANOVA	15	Zero	Large	Strength	26.7
ANOVA	15	Zero	Large	Power	30.3
ANOVA	15	Zero	Large	Sprint	34.5
ANOVA	15	Small	Small	Strength	43.5
ANOVA	15	Small	Small	Power	56
ANOVA	15	Small	Small	Sprint	73.6
ANOVA	15	Small	Medium	Strength	38.2
ANOVA	15	Small	Medium	Power	47
ANOVA	15	Small	Medium	Sprint	59.7
ANOVA	15	Small	Large	Strength	26.8
ANOVA	15	Small	Large	Power	30.2
ANOVA	15	Small	Large	Sprint	35.1
ANOVA	15	Medium	Small	Strength	43.7
ANOVA	15	Medium	Small	Power	55.9
ANOVA	15	Medium	Small	Sprint	73.7
ANOVA	15	Medium	Medium	Strength	38.1
ANOVA	15	Medium	Medium	Power	47
ANOVA	15	Medium	Medium	Sprint	60
ANOVA	15	Medium	Large	Strength	26.5
ANOVA	15	Medium	Large	Power	30
ANOVA	15	Medium	Large	Sprint	35.2

ANOVA	25	Zero	Small	Strength	64.1
ANOVA	25	Zero	Small	Power	78.6
ANOVA	25	Zero	Small	Sprint	92.2
ANOVA	25	Zero	Medium	Strength	56.9
ANOVA	25	Zero	Medium	Power	68.9
ANOVA	25	Zero	Medium	Sprint	81.9
ANOVA	25	Zero	Large	Strength	41
ANOVA	25	Zero	Large	Power	46.4
ANOVA	25	Zero	Large	Sprint	52.7
ANOVA	25	Small	Small	Strength	64
ANOVA	25	Small	Small	Power	78.1
ANOVA	25	Small	Small	Sprint	91.7
ANOVA	25	Small	Medium	Strength	56.9
ANOVA	25	Small	Medium	Power	68.8
ANOVA	25	Small	Medium	Sprint	81.4
ANOVA	25	Small	Large	Strength	40.7
ANOVA	25	Small	Large	Power	46.4
ANOVA	25	Small	Large	Sprint	52.8
ANOVA	25	Medium	Small	Strength	63.9
ANOVA	25	Medium	Small	Power	78.1
ANOVA	25	Medium	Small	Sprint	91.6
ANOVA	25	Medium	Medium	Strength	56.9
ANOVA	25	Medium	Medium	Power	68.5
ANOVA	25	Medium	Medium	Sprint	81.5
ANOVA	25	Medium	Large	Strength	40.3
ANOVA	25	Medium	Large	Power	46.1
ANOVA	25	Medium	Large	Sprint	53.1
ANOVA	50	Zero	Small	Strength	90.2
ANOVA	50	Zero	Small	Power	97.3
ANOVA	50	Zero	Small	Sprint	99.8
ANOVA	50	Zero	Medium	Strength	85.1
ANOVA	50	Zero	Medium	Power	93.3
ANOVA	50	Zero	Medium	Sprint	98.2
ANOVA	50	Zero	Large	Strength	67.7
ANOVA	50	Zero	Large	Power	75.3
ANOVA	50	Zero	Large	Sprint	81.6
ANOVA	50	Small	Small	Strength	90.5
ANOVA	50	Small	Small	Power	97.3
ANOVA	50	Small	Small	Sprint	99.7
ANOVA	50	Small	Medium	Strength	85
ANOVA	50	Small	Medium	Power	93.4
ANOVA	50	Small	Medium	Sprint	98.1
ANOVA	50	Small	Large	Strength	67.5
ANOVA	50	Small	Large	Power	75.1
ANOVA	50	Small	Large	Sprint	81.8
ANOVA	50	Medium	Small	Strength	90.4
ANOVA	50	Medium	Small	Power	97.3
ANOVA	50	Medium	Small	Sprint	99.8
ANOVA	50	Medium	Medium	Strength	85.1
ANOVA	50	Medium	Medium	Power	93.4

ANOVA	50	Medium	Medium	Sprint	98.2
ANOVA	50	Medium	Large	Strength	67.3
ANOVA	50	Medium	Large	Power	75.1
ANOVA	50	Medium	Large	Sprint	82
T-Test	10	Zero	Small	Strength	13.7
T-Test	10	Zero	Small	Power	14.5
T-Test	10	Zero	Small	Sprint	15.4
T-Test	10	Zero	Medium	Strength	13.3
T-Test	10	Zero	Medium	Power	14.2
T-Test	10	Zero	Medium	Sprint	14.9
T-Test	10	Zero	Large	Strength	12.5
T-Test	10	Zero	Large	Power	13
T-Test	10	Zero	Large	Sprint	13.7
T-Test	10	Small	Small	Strength	21.8
T-Test	10	Small	Small	Power	22.5
T-Test	10	Small	Small	Sprint	22.2
T-Test	10	Small	Medium	Strength	20.8
T-Test	10	Small	Medium	Power	21.3
T-Test	10	Small	Medium	Sprint	21.1
T-Test	10	Small	Large	Strength	18.2
T-Test	10	Small	Large	Power	18.5
T-Test	10	Small	Large	Sprint	18.3
T-Test	10	Medium	Small	Strength	32
T-Test	10	Medium	Small	Power	31.5
T-Test	10	Medium	Small	Sprint	29
T-Test	10	Medium	Medium	Strength	29.4
T-Test	10	Medium	Medium	Power	29
T-Test	10	Medium	Medium	Sprint	27.2
T-Test	10	Medium	Large	Strength	23.4
T-Test	10	Medium	Large	Power	22.7
T-Test	10	Medium	Large	Sprint	21.9
T-Test	15	Zero	Small	Strength	18.4
T-Test	15	Zero	Small	Power	19.7
T-Test	15	Zero	Small	Sprint	21.2
T-Test	15	Zero	Medium	Strength	17.9
T-Test	15	Zero	Medium	Power	19.3
T-Test	15	Zero	Medium	Sprint	20.6
T-Test	15	Zero	Large	Strength	16.6
T-Test	15	Zero	Large	Power	17.5
T-Test	15	Zero	Large	Sprint	18.5
T-Test	15	Small	Small	Strength	31.1
T-Test	15	Small	Small	Power	32.6
T-Test	15	Small	Small	Sprint	32.6
T-Test	15	Small	Medium	Strength	29.8
T-Test	15	Small	Medium	Power	30.7
T-Test	15	Small	Medium	Sprint	30.7
T-Test	15	Small	Large	Strength	25.6
T-Test	15	Small	Large	Power	25.9
T-Test	15	Small	Large	Sprint	26.1
T-Test	15	Medium	Small	Strength	46

T-Test	15	Medium	Small	Power	45.2
T-Test	15	Medium	Small	Sprint	42.8
T-Test	15	Medium	Medium	Strength	42.5
T-Test	15	Medium	Medium	Power	41.7
T-Test	15	Medium	Medium	Sprint	39.6
T-Test	15	Medium	Large	Strength	33.7
T-Test	15	Medium	Large	Power	32.8
T-Test	15	Medium	Large	Sprint	31.7
T-Test	25	Zero	Small	Strength	29.1
T-Test	25	Zero	Small	Power	31.1
T-Test	25	Zero	Small	Sprint	34.2
T-Test	25	Zero	Medium	Strength	28.2
T-Test	25	Zero	Medium	Power	30.1
T-Test	25	Zero	Medium	Sprint	33.1
T-Test	25	Zero	Large	Strength	26.2
T-Test	25	Zero	Large	Power	27.5
T-Test	25	Zero	Large	Sprint	29.4
T-Test	25	Small	Small	Strength	49
T-Test	25	Small	Small	Power	50.7
T-Test	25	Small	Small	Sprint	51.6
T-Test	25	Small	Medium	Strength	46.6
T-Test	25	Small	Medium	Power	48.2
T-Test	25	Small	Medium	Sprint	49
T-Test	25	Small	Large	Strength	40.2
T-Test	25	Small	Large	Power	40.7
T-Test	25	Small	Large	Sprint	41.4
T-Test	25	Medium	Small	Strength	68.6
T-Test	25	Medium	Small	Power	67.7
T-Test	25	Medium	Small	Sprint	65.1
T-Test	25	Medium	Medium	Strength	64.5
T-Test	25	Medium	Medium	Power	63.6
T-Test	25	Medium	Medium	Sprint	61.3
T-Test	25	Medium	Large	Strength	52.6
T-Test	25	Medium	Large	Power	51.3
T-Test	25	Medium	Large	Sprint	49.7
T-Test	50	Zero	Small	Strength	50.8
T-Test	50	Zero	Small	Power	55.5
T-Test	50	Zero	Small	Sprint	59.6
T-Test	50	Zero	Medium	Strength	49.4
T-Test	50	Zero	Medium	Power	54
T-Test	50	Zero	Medium	Sprint	57.6
T-Test	50	Zero	Large	Strength	45.5
T-Test	50	Zero	Large	Power	49.2
T-Test	50	Zero	Large	Sprint	52.4
T-Test	50	Small	Small	Strength	78.2
T-Test	50	Small	Small	Power	81.1
T-Test	50	Small	Small	Sprint	80.9
T-Test	50	Small	Medium	Strength	75.8
T-Test	50	Small	Medium	Power	78.6
T-Test	50	Small	Medium	Sprint	78.3

T-Test	50	Small	Large	Strength	67.5
T-Test	50	Small	Large	Power	69.4
T-Test	50	Small	Large	Sprint	69.5
T-Test	50	Medium	Small	Strength	93.4
T-Test	50	Medium	Small	Power	93.5
T-Test	50	Medium	Small	Sprint	91.6
T-Test	50	Medium	Medium	Strength	91.2
T-Test	50	Medium	Medium	Power	91.2
T-Test	50	Medium	Medium	Sprint	89
T-Test	50	Medium	Large	Strength	81.6
T-Test	50	Medium	Large	Power	81.5
T-Test	50	Medium	Large	Sprint	79.3

Large ATE and Positive Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	27.5
ANCOVA	10	Zero	Small	Power	35.6
ANCOVA	10	Zero	Small	Sprint	50
ANCOVA	10	Zero	Medium	Strength	26.3
ANCOVA	10	Zero	Medium	Power	32.8
ANCOVA	10	Zero	Medium	Sprint	42.7
ANCOVA	10	Zero	Large	Strength	24.1
ANCOVA	10	Zero	Large	Power	27.1
ANCOVA	10	Zero	Large	Sprint	32.2
ANCOVA	10	Small	Small	Strength	34.6
ANCOVA	10	Small	Small	Power	45
ANCOVA	10	Small	Small	Sprint	61.8
ANCOVA	10	Small	Medium	Strength	32
ANCOVA	10	Small	Medium	Power	40.3
ANCOVA	10	Small	Medium	Sprint	51.9
ANCOVA	10	Small	Large	Strength	27.2
ANCOVA	10	Small	Large	Power	31.2
ANCOVA	10	Small	Large	Sprint	36.4
ANCOVA	10	Medium	Small	Strength	46.9
ANCOVA	10	Medium	Small	Power	60.4
ANCOVA	10	Medium	Small	Sprint	78
ANCOVA	10	Medium	Medium	Strength	42.4
ANCOVA	10	Medium	Medium	Power	51.2
ANCOVA	10	Medium	Medium	Sprint	63.1
ANCOVA	10	Medium	Large	Strength	32.1
ANCOVA	10	Medium	Large	Power	36.2
ANCOVA	10	Medium	Large	Sprint	41
ANCOVA	15	Zero	Small	Strength	39.7
ANCOVA	15	Zero	Small	Power	52.1
ANCOVA	15	Zero	Small	Sprint	70
ANCOVA	15	Zero	Medium	Strength	38
ANCOVA	15	Zero	Medium	Power	47.6
ANCOVA	15	Zero	Medium	Sprint	60.7
ANCOVA	15	Zero	Large	Strength	34.3
ANCOVA	15	Zero	Large	Power	39.6
ANCOVA	15	Zero	Large	Sprint	46.6

ANCOVA	15	Small	Small	Strength	49.8
ANCOVA	15	Small	Small	Power	64.2
ANCOVA	15	Small	Small	Sprint	81.5
ANCOVA	15	Small	Medium	Strength	46.4
ANCOVA	15	Small	Medium	Power	57.8
ANCOVA	15	Small	Medium	Sprint	71.3
ANCOVA	15	Small	Large	Strength	39.1
ANCOVA	15	Small	Large	Power	45.6
ANCOVA	15	Small	Large	Sprint	52.4
ANCOVA	15	Medium	Small	Strength	66
ANCOVA	15	Medium	Small	Power	80.3
ANCOVA	15	Medium	Small	Sprint	93.3
ANCOVA	15	Medium	Medium	Strength	59.8
ANCOVA	15	Medium	Medium	Power	71
ANCOVA	15	Medium	Medium	Sprint	82.3
ANCOVA	15	Medium	Large	Strength	46.2
ANCOVA	15	Medium	Large	Power	52
ANCOVA	15	Medium	Large	Sprint	58.5
ANCOVA	25	Zero	Small	Strength	61.1
ANCOVA	25	Zero	Small	Power	75.6
ANCOVA	25	Zero	Small	Sprint	90.3
ANCOVA	25	Zero	Medium	Strength	58.5
ANCOVA	25	Zero	Medium	Power	70.6
ANCOVA	25	Zero	Medium	Sprint	83.3
ANCOVA	25	Zero	Large	Strength	53.2
ANCOVA	25	Zero	Large	Power	60.8
ANCOVA	25	Zero	Large	Sprint	68.9
ANCOVA	25	Small	Small	Strength	73.2
ANCOVA	25	Small	Small	Power	86.3
ANCOVA	25	Small	Small	Sprint	96.3
ANCOVA	25	Small	Medium	Strength	69.6
ANCOVA	25	Small	Medium	Power	80.8
ANCOVA	25	Small	Medium	Sprint	91.1
ANCOVA	25	Small	Large	Strength	60
ANCOVA	25	Small	Large	Power	68
ANCOVA	25	Small	Large	Sprint	74.9
ANCOVA	25	Medium	Small	Strength	87.7
ANCOVA	25	Medium	Small	Power	95.8
ANCOVA	25	Medium	Small	Sprint	99.4
ANCOVA	25	Medium	Medium	Strength	82.8
ANCOVA	25	Medium	Medium	Power	91.1
ANCOVA	25	Medium	Medium	Sprint	96.4
ANCOVA	25	Medium	Large	Strength	69.1
ANCOVA	25	Medium	Large	Power	75.2
ANCOVA	25	Medium	Large	Sprint	81.2
ANCOVA	50	Zero	Small	Strength	88.7
ANCOVA	50	Zero	Small	Power	96.4
ANCOVA	50	Zero	Small	Sprint	99.6
ANCOVA	50	Zero	Medium	Strength	86.8
ANCOVA	50	Zero	Medium	Power	94.5

ANCOVA	50	Zero	Medium	Sprint	98.6
ANCOVA	50	Zero	Large	Strength	82.7
ANCOVA	50	Zero	Large	Power	88.6
ANCOVA	50	Zero	Large	Sprint	93.6
ANCOVA	50	Small	Small	Strength	95.5
ANCOVA	50	Small	Small	Power	99.3
ANCOVA	50	Small	Small	Sprint	100
ANCOVA	50	Small	Medium	Strength	93.7
ANCOVA	50	Small	Medium	Power	98
ANCOVA	50	Small	Medium	Sprint	99.7
ANCOVA	50	Small	Large	Strength	88.2
ANCOVA	50	Small	Large	Power	93
ANCOVA	50	Small	Large	Sprint	96.4
ANCOVA	50	Medium	Small	Strength	99.3
ANCOVA	50	Medium	Small	Power	99.9
ANCOVA	50	Medium	Small	Sprint	100
ANCOVA	50	Medium	Medium	Strength	98.5
ANCOVA	50	Medium	Medium	Power	99.7
ANCOVA	50	Medium	Medium	Sprint	100
ANCOVA	50	Medium	Large	Strength	93.4
ANCOVA	50	Medium	Large	Power	96.4
ANCOVA	50	Medium	Large	Sprint	98.1
ANOVA	10	Zero	Small	Strength	31.5
ANOVA	10	Zero	Small	Power	40.3
ANOVA	10	Zero	Small	Sprint	55.6
ANOVA	10	Zero	Medium	Strength	27.5
ANOVA	10	Zero	Medium	Power	33.7
ANOVA	10	Zero	Medium	Sprint	43.6
ANOVA	10	Zero	Large	Strength	19.9
ANOVA	10	Zero	Large	Power	22.4
ANOVA	10	Zero	Large	Sprint	25
ANOVA	10	Small	Small	Strength	12.9
ANOVA	10	Small	Small	Power	19.9
ANOVA	10	Small	Small	Sprint	33.6
ANOVA	10	Small	Medium	Strength	11.8
ANOVA	10	Small	Medium	Power	16.8
ANOVA	10	Small	Medium	Sprint	25.8
ANOVA	10	Small	Large	Strength	9.4
ANOVA	10	Small	Large	Power	12.2
ANOVA	10	Small	Large	Sprint	15.7
ANOVA	10	Medium	Small	Strength	5.4
ANOVA	10	Medium	Small	Power	10.5
ANOVA	10	Medium	Small	Sprint	23.1
ANOVA	10	Medium	Medium	Strength	5.5
ANOVA	10	Medium	Medium	Power	9.5
ANOVA	10	Medium	Medium	Sprint	17.9
ANOVA	10	Medium	Large	Strength	6
ANOVA	10	Medium	Large	Power	8.2
ANOVA	10	Medium	Large	Sprint	11.9
ANOVA	15	Zero	Small	Strength	43.2

ANOVA	15	Zero	Small	Power	56.2
ANOVA	15	Zero	Small	Sprint	74.1
ANOVA	15	Zero	Medium	Strength	38
ANOVA	15	Zero	Medium	Power	47.1
ANOVA	15	Zero	Medium	Sprint	60.2
ANOVA	15	Zero	Large	Strength	26.6
ANOVA	15	Zero	Large	Power	30.6
ANOVA	15	Zero	Large	Sprint	34.8
ANOVA	15	Small	Small	Strength	17.8
ANOVA	15	Small	Small	Power	28.9
ANOVA	15	Small	Small	Sprint	50.1
ANOVA	15	Small	Medium	Strength	15.7
ANOVA	15	Small	Medium	Power	23.6
ANOVA	15	Small	Medium	Sprint	37.2
ANOVA	15	Small	Large	Strength	11.9
ANOVA	15	Small	Large	Power	15.9
ANOVA	15	Small	Large	Sprint	21.4
ANOVA	15	Medium	Small	Strength	7.3
ANOVA	15	Medium	Small	Power	15.6
ANOVA	15	Medium	Small	Sprint	36.6
ANOVA	15	Medium	Medium	Strength	7.2
ANOVA	15	Medium	Medium	Power	14
ANOVA	15	Medium	Medium	Sprint	27.1
ANOVA	15	Medium	Large	Strength	6.7
ANOVA	15	Medium	Large	Power	10.5
ANOVA	15	Medium	Large	Sprint	15.9
ANOVA	25	Zero	Small	Strength	64.1
ANOVA	25	Zero	Small	Power	78.3
ANOVA	25	Zero	Small	Sprint	92.2
ANOVA	25	Zero	Medium	Strength	57.3
ANOVA	25	Zero	Medium	Power	69
ANOVA	25	Zero	Medium	Sprint	81.8
ANOVA	25	Zero	Large	Strength	40.8
ANOVA	25	Zero	Large	Power	46.7
ANOVA	25	Zero	Large	Sprint	52.9
ANOVA	25	Small	Small	Strength	28.7
ANOVA	25	Small	Small	Power	47.2
ANOVA	25	Small	Small	Sprint	74.4
ANOVA	25	Small	Medium	Strength	25.1
ANOVA	25	Small	Medium	Power	38.2
ANOVA	25	Small	Medium	Sprint	58.6
ANOVA	25	Small	Large	Strength	18
ANOVA	25	Small	Large	Power	24.2
ANOVA	25	Small	Large	Sprint	33.2
ANOVA	25	Medium	Small	Strength	12.7
ANOVA	25	Medium	Small	Power	28.8
ANOVA	25	Medium	Small	Sprint	62.3
ANOVA	25	Medium	Medium	Strength	11.6
ANOVA	25	Medium	Medium	Power	23.7
ANOVA	25	Medium	Medium	Sprint	45.6

ANOVA	25	Medium	Large	Strength	9.6
ANOVA	25	Medium	Large	Power	15.7
ANOVA	25	Medium	Large	Sprint	24.7
ANOVA	50	Zero	Small	Strength	90.2
ANOVA	50	Zero	Small	Power	97.2
ANOVA	50	Zero	Small	Sprint	99.8
ANOVA	50	Zero	Medium	Strength	85
ANOVA	50	Zero	Medium	Power	93.4
ANOVA	50	Zero	Medium	Sprint	98.3
ANOVA	50	Zero	Large	Strength	67.3
ANOVA	50	Zero	Large	Power	75.3
ANOVA	50	Zero	Large	Sprint	81.7
ANOVA	50	Small	Small	Strength	54
ANOVA	50	Small	Small	Power	79.1
ANOVA	50	Small	Small	Sprint	96.8
ANOVA	50	Small	Medium	Strength	46.4
ANOVA	50	Small	Medium	Power	67.9
ANOVA	50	Small	Medium	Sprint	88.3
ANOVA	50	Small	Large	Strength	31.6
ANOVA	50	Small	Large	Power	44.2
ANOVA	50	Small	Large	Sprint	58.3
ANOVA	50	Medium	Small	Strength	28.3
ANOVA	50	Medium	Small	Power	61.5
ANOVA	50	Medium	Small	Sprint	93.7
ANOVA	50	Medium	Medium	Strength	24.1
ANOVA	50	Medium	Medium	Power	49.2
ANOVA	50	Medium	Medium	Sprint	79.2
ANOVA	50	Medium	Large	Strength	17.2
ANOVA	50	Medium	Large	Power	29.6
ANOVA	50	Medium	Large	Sprint	45.9
T-Test	10	Zero	Small	Strength	35.9
T-Test	10	Zero	Small	Power	40.7
T-Test	10	Zero	Small	Sprint	46.8
T-Test	10	Zero	Medium	Strength	34.8
T-Test	10	Zero	Medium	Power	38.9
T-Test	10	Zero	Medium	Sprint	44.5
T-Test	10	Zero	Large	Strength	30.7
T-Test	10	Zero	Large	Power	33.7
T-Test	10	Zero	Large	Sprint	37.6
T-Test	10	Small	Small	Strength	47.7
T-Test	10	Small	Small	Power	54
T-Test	10	Small	Small	Sprint	61.5
T-Test	10	Small	Medium	Strength	44.8
T-Test	10	Small	Medium	Power	50.4
T-Test	10	Small	Medium	Sprint	56.8
T-Test	10	Small	Large	Strength	36.8
T-Test	10	Small	Large	Power	40.8
T-Test	10	Small	Large	Sprint	45.1
T-Test	10	Medium	Small	Strength	61.3
T-Test	10	Medium	Small	Power	68.4

T-Test	10	Medium	Small	Sprint	74.1
T-Test	10	Medium	Medium	Strength	55.9
T-Test	10	Medium	Medium	Power	62.5
T-Test	10	Medium	Medium	Sprint	67.3
T-Test	10	Medium	Large	Strength	43
T-Test	10	Medium	Large	Power	47.4
T-Test	10	Medium	Large	Sprint	50.5
T-Test	15	Zero	Small	Strength	60
T-Test	15	Zero	Small	Power	68.6
T-Test	15	Zero	Small	Sprint	77
T-Test	15	Zero	Medium	Strength	57.7
T-Test	15	Zero	Medium	Power	65.5
T-Test	15	Zero	Medium	Sprint	73.5
T-Test	15	Zero	Large	Strength	51
T-Test	15	Zero	Large	Power	57.2
T-Test	15	Zero	Large	Sprint	63
T-Test	15	Small	Small	Strength	71.2
T-Test	15	Small	Small	Power	80.8
T-Test	15	Small	Small	Sprint	88.3
T-Test	15	Small	Medium	Strength	67.6
T-Test	15	Small	Medium	Power	76.5
T-Test	15	Small	Medium	Sprint	84
T-Test	15	Small	Large	Strength	56.6
T-Test	15	Small	Large	Power	63.7
T-Test	15	Small	Large	Sprint	70.3
T-Test	15	Medium	Small	Strength	83.8
T-Test	15	Medium	Small	Power	91.3
T-Test	15	Medium	Small	Sprint	95.3
T-Test	15	Medium	Medium	Strength	78.7
T-Test	15	Medium	Medium	Power	86.4
T-Test	15	Medium	Medium	Sprint	91.2
T-Test	15	Medium	Large	Strength	63.2
T-Test	15	Medium	Large	Power	70.3
T-Test	15	Medium	Large	Sprint	75
T-Test	25	Zero	Small	Strength	90.1
T-Test	25	Zero	Small	Power	95.5
T-Test	25	Zero	Small	Sprint	98.4
T-Test	25	Zero	Medium	Strength	88.4
T-Test	25	Zero	Medium	Power	93.9
T-Test	25	Zero	Medium	Sprint	97.4
T-Test	25	Zero	Large	Strength	81.6
T-Test	25	Zero	Large	Power	87.7
T-Test	25	Zero	Large	Sprint	92.3
T-Test	25	Small	Small	Strength	94.2
T-Test	25	Small	Small	Power	98.1
T-Test	25	Small	Small	Sprint	99.6
T-Test	25	Small	Medium	Strength	92
T-Test	25	Small	Medium	Power	96.9
T-Test	25	Small	Medium	Sprint	99
T-Test	25	Small	Large	Strength	83.3

T-Test	25	Small	Large	Power	89.8
T-Test	25	Small	Large	Sprint	94.1
T-Test	25	Medium	Small	Strength	98.2
T-Test	25	Medium	Small	Power	99.7
T-Test	25	Medium	Small	Sprint	100
T-Test	25	Medium	Medium	Strength	96.5
T-Test	25	Medium	Medium	Power	99
T-Test	25	Medium	Medium	Sprint	99.8
T-Test	25	Medium	Large	Strength	87.9
T-Test	25	Medium	Large	Power	93.1
T-Test	25	Medium	Large	Sprint	95.8
T-Test	50	Zero	Small	Strength	99.9
T-Test	50	Zero	Small	Power	100
T-Test	50	Zero	Small	Sprint	100
T-Test	50	Zero	Medium	Strength	99.8
T-Test	50	Zero	Medium	Power	100
T-Test	50	Zero	Medium	Sprint	100
T-Test	50	Zero	Large	Strength	99.4
T-Test	50	Zero	Large	Power	99.9
T-Test	50	Zero	Large	Sprint	100
T-Test	50	Small	Small	Strength	100
T-Test	50	Small	Small	Power	100
T-Test	50	Small	Small	Sprint	100
T-Test	50	Small	Medium	Strength	99.9
T-Test	50	Small	Medium	Power	100
T-Test	50	Small	Medium	Sprint	100
T-Test	50	Small	Large	Strength	99.3
T-Test	50	Small	Large	Power	99.9
T-Test	50	Small	Large	Sprint	100
T-Test	50	Medium	Small	Strength	100
T-Test	50	Medium	Small	Power	100
T-Test	50	Medium	Small	Sprint	100
T-Test	50	Medium	Medium	Strength	100
T-Test	50	Medium	Medium	Power	100
T-Test	50	Medium	Medium	Sprint	100
T-Test	50	Medium	Large	Strength	99.6
T-Test	50	Medium	Large	Power	99.9
T-Test	50	Medium	Large	Sprint	100

Large ATE and 50egative Imbalance

Test	SampleSize	IDE	Error	Outcome	P005
ANCOVA	10	Zero	Small	Strength	26.4
ANCOVA	10	Zero	Small	Power	34.3
ANCOVA	10	Zero	Small	Sprint	48.4
ANCOVA	10	Zero	Medium	Strength	20.9
ANCOVA	10	Zero	Medium	Power	25.8
ANCOVA	10	Zero	Medium	Sprint	33.6
ANCOVA	10	Zero	Large	Strength	11.8
ANCOVA	10	Zero	Large	Power	13
ANCOVA	10	Zero	Large	Sprint	14.8

ANCOVA	10	Small	Small	Strength	33
ANCOVA	10	Small	Small	Power	44.1
ANCOVA	10	Small	Small	Sprint	60.6
ANCOVA	10	Small	Medium	Strength	27.4
ANCOVA	10	Small	Medium	Power	34.5
ANCOVA	10	Small	Medium	Sprint	44
ANCOVA	10	Small	Large	Strength	16.8
ANCOVA	10	Small	Large	Power	18.7
ANCOVA	10	Small	Large	Sprint	20
ANCOVA	10	Medium	Small	Strength	46.3
ANCOVA	10	Medium	Small	Power	59.3
ANCOVA	10	Medium	Small	Sprint	76.8
ANCOVA	10	Medium	Medium	Strength	37.9
ANCOVA	10	Medium	Medium	Power	45.5
ANCOVA	10	Medium	Medium	Sprint	55.7
ANCOVA	10	Medium	Large	Strength	22.5
ANCOVA	10	Medium	Large	Power	23.6
ANCOVA	10	Medium	Large	Sprint	24.4
ANCOVA	15	Zero	Small	Strength	38.2
ANCOVA	15	Zero	Small	Power	50.7
ANCOVA	15	Zero	Small	Sprint	68.4
ANCOVA	15	Zero	Medium	Strength	30.8
ANCOVA	15	Zero	Medium	Power	38.9
ANCOVA	15	Zero	Medium	Sprint	50.1
ANCOVA	15	Zero	Large	Strength	16.5
ANCOVA	15	Zero	Large	Power	18.7
ANCOVA	15	Zero	Large	Sprint	21.8
ANCOVA	15	Small	Small	Strength	48.1
ANCOVA	15	Small	Small	Power	62.8
ANCOVA	15	Small	Small	Sprint	79.8
ANCOVA	15	Small	Medium	Strength	40.5
ANCOVA	15	Small	Medium	Power	50.5
ANCOVA	15	Small	Medium	Sprint	62.7
ANCOVA	15	Small	Large	Strength	24.5
ANCOVA	15	Small	Large	Power	27.4
ANCOVA	15	Small	Large	Sprint	30
ANCOVA	15	Medium	Small	Strength	65.1
ANCOVA	15	Medium	Small	Power	79.7
ANCOVA	15	Medium	Small	Sprint	92.6
ANCOVA	15	Medium	Medium	Strength	55.1
ANCOVA	15	Medium	Medium	Power	65.2
ANCOVA	15	Medium	Medium	Sprint	76.2
ANCOVA	15	Medium	Large	Strength	32.7
ANCOVA	15	Medium	Large	Power	35
ANCOVA	15	Medium	Large	Sprint	37
ANCOVA	25	Zero	Small	Strength	59
ANCOVA	25	Zero	Small	Power	74
ANCOVA	25	Zero	Small	Sprint	89.3
ANCOVA	25	Zero	Medium	Strength	48.6
ANCOVA	25	Zero	Medium	Power	59.9

ANCOVA	25	Zero	Medium	Sprint	73.8
ANCOVA	25	Zero	Large	Strength	26.2
ANCOVA	25	Zero	Large	Power	30.7
ANCOVA	25	Zero	Large	Sprint	35.8
ANCOVA	25	Small	Small	Strength	71.2
ANCOVA	25	Small	Small	Power	85.2
ANCOVA	25	Small	Small	Sprint	95.7
ANCOVA	25	Small	Medium	Strength	62
ANCOVA	25	Small	Medium	Power	74
ANCOVA	25	Small	Medium	Sprint	85.3
ANCOVA	25	Small	Large	Strength	39.1
ANCOVA	25	Small	Large	Power	44.1
ANCOVA	25	Small	Large	Sprint	48.4
ANCOVA	25	Medium	Small	Strength	87.1
ANCOVA	25	Medium	Small	Power	95.7
ANCOVA	25	Medium	Small	Sprint	99.5
ANCOVA	25	Medium	Medium	Strength	78.4
ANCOVA	25	Medium	Medium	Power	87.5
ANCOVA	25	Medium	Medium	Sprint	94.2
ANCOVA	25	Medium	Large	Strength	52.2
ANCOVA	25	Medium	Large	Power	56.1
ANCOVA	25	Medium	Large	Sprint	58.1
ANCOVA	50	Zero	Small	Strength	87.2
ANCOVA	50	Zero	Small	Power	96.1
ANCOVA	50	Zero	Small	Sprint	99.6
ANCOVA	50	Zero	Medium	Strength	77.9
ANCOVA	50	Zero	Medium	Power	88.6
ANCOVA	50	Zero	Medium	Sprint	96.1
ANCOVA	50	Zero	Large	Strength	48
ANCOVA	50	Zero	Large	Power	55.4
ANCOVA	50	Zero	Large	Sprint	63.5
ANCOVA	50	Small	Small	Strength	94.8
ANCOVA	50	Small	Small	Power	99
ANCOVA	50	Small	Small	Sprint	100
ANCOVA	50	Small	Medium	Strength	90.1
ANCOVA	50	Small	Medium	Power	96
ANCOVA	50	Small	Medium	Sprint	99.1
ANCOVA	50	Small	Large	Strength	68.4
ANCOVA	50	Small	Large	Power	74.3
ANCOVA	50	Small	Large	Sprint	79.4
ANCOVA	50	Medium	Small	Strength	99.3
ANCOVA	50	Medium	Small	Power	100
ANCOVA	50	Medium	Small	Sprint	100
ANCOVA	50	Medium	Medium	Strength	97.6
ANCOVA	50	Medium	Medium	Power	99.4
ANCOVA	50	Medium	Medium	Sprint	99.9
ANCOVA	50	Medium	Large	Strength	82.3
ANCOVA	50	Medium	Large	Power	85.7
ANCOVA	50	Medium	Large	Sprint	87.9
ANOVA	10	Zero	Small	Strength	31.5

ANOVA	10	Zero	Small	Power	40.4
ANOVA	10	Zero	Small	Sprint	55.6
ANOVA	10	Zero	Medium	Strength	27.5
ANOVA	10	Zero	Medium	Power	33.6
ANOVA	10	Zero	Medium	Sprint	43.3
ANOVA	10	Zero	Large	Strength	19.7
ANOVA	10	Zero	Large	Power	22
ANOVA	10	Zero	Large	Sprint	25.2
ANOVA	10	Small	Small	Strength	50.6
ANOVA	10	Small	Small	Power	62.6
ANOVA	10	Small	Small	Sprint	77
ANOVA	10	Small	Medium	Strength	43.8
ANOVA	10	Small	Medium	Power	52.5
ANOVA	10	Small	Medium	Sprint	61.4
ANOVA	10	Small	Large	Strength	30.5
ANOVA	10	Small	Large	Power	33.4
ANOVA	10	Small	Large	Sprint	35.4
ANOVA	10	Medium	Small	Strength	62.7
ANOVA	10	Medium	Small	Power	74.1
ANOVA	10	Medium	Small	Sprint	87.1
ANOVA	10	Medium	Medium	Strength	53.8
ANOVA	10	Medium	Medium	Power	61.2
ANOVA	10	Medium	Medium	Sprint	70.7
ANOVA	10	Medium	Large	Strength	36
ANOVA	10	Medium	Large	Power	38.5
ANOVA	10	Medium	Large	Sprint	39.6
ANOVA	15	Zero	Small	Strength	43.2
ANOVA	15	Zero	Small	Power	56.5
ANOVA	15	Zero	Small	Sprint	74
ANOVA	15	Zero	Medium	Strength	37.8
ANOVA	15	Zero	Medium	Power	47.2
ANOVA	15	Zero	Medium	Sprint	60.1
ANOVA	15	Zero	Large	Strength	26.7
ANOVA	15	Zero	Large	Power	30.4
ANOVA	15	Zero	Large	Sprint	35
ANOVA	15	Small	Small	Strength	69.9
ANOVA	15	Small	Small	Power	81.8
ANOVA	15	Small	Small	Sprint	92.4
ANOVA	15	Small	Medium	Strength	61.9
ANOVA	15	Small	Medium	Power	71.5
ANOVA	15	Small	Medium	Sprint	80.3
ANOVA	15	Small	Large	Strength	43.3
ANOVA	15	Small	Large	Power	47.1
ANOVA	15	Small	Large	Sprint	49.7
ANOVA	15	Medium	Small	Strength	83.9
ANOVA	15	Medium	Small	Power	92.3
ANOVA	15	Medium	Small	Sprint	97.8
ANOVA	15	Medium	Medium	Strength	74.9
ANOVA	15	Medium	Medium	Power	82.1
ANOVA	15	Medium	Medium	Sprint	89

ANOVA	15	Medium	Large	Strength	52.5
ANOVA	15	Medium	Large	Power	55.3
ANOVA	15	Medium	Large	Sprint	56.9
ANOVA	25	Zero	Small	Strength	64.1
ANOVA	25	Zero	Small	Power	78.5
ANOVA	25	Zero	Small	Sprint	92.3
ANOVA	25	Zero	Medium	Strength	57.1
ANOVA	25	Zero	Medium	Power	68.9
ANOVA	25	Zero	Medium	Sprint	81.8
ANOVA	25	Zero	Large	Strength	41.1
ANOVA	25	Zero	Large	Power	46.8
ANOVA	25	Zero	Large	Sprint	52.9
ANOVA	25	Small	Small	Strength	91.2
ANOVA	25	Small	Small	Power	96.8
ANOVA	25	Small	Small	Sprint	99.5
ANOVA	25	Small	Medium	Strength	85.2
ANOVA	25	Small	Medium	Power	91.6
ANOVA	25	Small	Medium	Sprint	95.9
ANOVA	25	Small	Large	Strength	65.6
ANOVA	25	Small	Large	Power	69.5
ANOVA	25	Small	Large	Sprint	72.3
ANOVA	25	Medium	Small	Strength	98.3
ANOVA	25	Medium	Small	Power	99.6
ANOVA	25	Medium	Small	Sprint	100
ANOVA	25	Medium	Medium	Strength	94.7
ANOVA	25	Medium	Medium	Power	97.4
ANOVA	25	Medium	Medium	Sprint	98.9
ANOVA	25	Medium	Large	Strength	77.3
ANOVA	25	Medium	Large	Power	79.3
ANOVA	25	Medium	Large	Sprint	80.3
ANOVA	50	Zero	Small	Strength	90.2
ANOVA	50	Zero	Small	Power	97.4
ANOVA	50	Zero	Small	Sprint	99.8
ANOVA	50	Zero	Medium	Strength	84.9
ANOVA	50	Zero	Medium	Power	93.5
ANOVA	50	Zero	Medium	Sprint	98.1
ANOVA	50	Zero	Large	Strength	67.6
ANOVA	50	Zero	Large	Power	75.2
ANOVA	50	Zero	Large	Sprint	82
ANOVA	50	Small	Small	Strength	99.8
ANOVA	50	Small	Small	Power	100
ANOVA	50	Small	Small	Sprint	100
ANOVA	50	Small	Medium	Strength	99.1
ANOVA	50	Small	Medium	Power	99.8
ANOVA	50	Small	Medium	Sprint	100
ANOVA	50	Small	Large	Strength	92.7
ANOVA	50	Small	Large	Power	94.4
ANOVA	50	Small	Large	Sprint	95.4
ANOVA	50	Medium	Small	Strength	100
ANOVA	50	Medium	Small	Power	100

ANOVA	50	Medium	Small	Sprint	100
ANOVA	50	Medium	Medium	Strength	100
ANOVA	50	Medium	Medium	Power	100
ANOVA	50	Medium	Medium	Sprint	100
ANOVA	50	Medium	Large	Strength	97.7
ANOVA	50	Medium	Large	Power	98.1
ANOVA	50	Medium	Large	Sprint	98.3
T-Test	10	Zero	Small	Strength	0.4
T-Test	10	Zero	Small	Power	0.1
T-Test	10	Zero	Small	Sprint	0.1
T-Test	10	Zero	Medium	Strength	0.4
T-Test	10	Zero	Medium	Power	0.2
T-Test	10	Zero	Medium	Sprint	0.1
T-Test	10	Zero	Large	Strength	0.7
T-Test	10	Zero	Large	Power	0.4
T-Test	10	Zero	Large	Sprint	0.3
T-Test	10	Small	Small	Strength	2.5
T-Test	10	Small	Small	Power	1.2
T-Test	10	Small	Small	Sprint	0.4
T-Test	10	Small	Medium	Strength	2.7
T-Test	10	Small	Medium	Power	1.4
T-Test	10	Small	Medium	Sprint	0.5
T-Test	10	Small	Large	Strength	3
T-Test	10	Small	Large	Power	1.9
T-Test	10	Small	Large	Sprint	1.1
T-Test	10	Medium	Small	Strength	7.3
T-Test	10	Medium	Small	Power	3.2
T-Test	10	Medium	Small	Sprint	0.9
T-Test	10	Medium	Medium	Strength	7.2
T-Test	10	Medium	Medium	Power	3.4
T-Test	10	Medium	Medium	Sprint	1.2
T-Test	10	Medium	Large	Strength	6.8
T-Test	10	Medium	Large	Power	3.9
T-Test	10	Medium	Large	Sprint	2
T-Test	15	Zero	Small	Strength	0.3
T-Test	15	Zero	Small	Power	0.1
T-Test	15	Zero	Small	Sprint	0
T-Test	15	Zero	Medium	Strength	0.4
T-Test	15	Zero	Medium	Power	0.1
T-Test	15	Zero	Medium	Sprint	0
T-Test	15	Zero	Large	Strength	0.6
T-Test	15	Zero	Large	Power	0.3
T-Test	15	Zero	Large	Sprint	0.2
T-Test	15	Small	Small	Strength	3.1
T-Test	15	Small	Small	Power	1.4
T-Test	15	Small	Small	Sprint	0.4
T-Test	15	Small	Medium	Strength	3.1
T-Test	15	Small	Medium	Power	1.5
T-Test	15	Small	Medium	Sprint	0.5
T-Test	15	Small	Large	Strength	3.6

T-Test	15	Small	Large	Power	2.2
T-Test	15	Small	Large	Sprint	1.1
T-Test	15	Medium	Small	Strength	10.8
T-Test	15	Medium	Small	Power	4.5
T-Test	15	Medium	Small	Sprint	0.9
T-Test	15	Medium	Medium	Strength	10.4
T-Test	15	Medium	Medium	Power	4.9
T-Test	15	Medium	Medium	Sprint	1.4
T-Test	15	Medium	Large	Strength	9.4
T-Test	15	Medium	Large	Power	5.4
T-Test	15	Medium	Large	Sprint	2.4
T-Test	25	Zero	Small	Strength	0.2
T-Test	25	Zero	Small	Power	0.1
T-Test	25	Zero	Small	Sprint	0
T-Test	25	Zero	Medium	Strength	0.3
T-Test	25	Zero	Medium	Power	0.1
T-Test	25	Zero	Medium	Sprint	0
T-Test	25	Zero	Large	Strength	0.5
T-Test	25	Zero	Large	Power	0.3
T-Test	25	Zero	Large	Sprint	0.1
T-Test	25	Small	Small	Strength	4.8
T-Test	25	Small	Small	Power	2.1
T-Test	25	Small	Small	Sprint	0.5
T-Test	25	Small	Medium	Strength	4.8
T-Test	25	Small	Medium	Power	2.4
T-Test	25	Small	Medium	Sprint	0.6
T-Test	25	Small	Large	Strength	4.8
T-Test	25	Small	Large	Power	2.9
T-Test	25	Small	Large	Sprint	1.4
T-Test	25	Medium	Small	Strength	19.8
T-Test	25	Medium	Small	Power	9
T-Test	25	Medium	Small	Sprint	1.9
T-Test	25	Medium	Medium	Strength	18.5
T-Test	25	Medium	Medium	Power	9.2
T-Test	25	Medium	Medium	Sprint	2.5
T-Test	25	Medium	Large	Strength	15
T-Test	25	Medium	Large	Power	8.7
T-Test	25	Medium	Large	Sprint	3.6
T-Test	50	Zero	Small	Strength	0.1
T-Test	50	Zero	Small	Power	0.1
T-Test	50	Zero	Small	Sprint	0
T-Test	50	Zero	Medium	Strength	0.2
T-Test	50	Zero	Medium	Power	0.1
T-Test	50	Zero	Medium	Sprint	0
T-Test	50	Zero	Large	Strength	0.4
T-Test	50	Zero	Large	Power	0.2
T-Test	50	Zero	Large	Sprint	0.1
T-Test	50	Small	Small	Strength	10.3
T-Test	50	Small	Small	Power	4.7
T-Test	50	Small	Small	Sprint	1

T-Test	50	Small	Medium	Strength	10.1
T-Test	50	Small	Medium	Power	5
T-Test	50	Small	Medium	Sprint	1.4
T-Test	50	Small	Large	Strength	9.3
T-Test	50	Small	Large	Power	5.4
T-Test	50	Small	Large	Sprint	2.3
T-Test	50	Medium	Small	Strength	43.6
T-Test	50	Medium	Small	Power	24.8
T-Test	50	Medium	Small	Sprint	6.4
T-Test	50	Medium	Medium	Strength	39.4
T-Test	50	Medium	Medium	Power	23.1
T-Test	50	Medium	Medium	Sprint	7.4
T-Test	50	Medium	Large	Strength	30.2
T-Test	50	Medium	Large	Power	18.5
T-Test	50	Medium	Large	Sprint	8.1