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The Benefits of Using Semi-continuous and Continuous Models to Analyze Binge Eating Data: A Monte Carlo Investigation

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Abstract

Objective—Change in binge eating is typically a primary outcome for interventions targeting individuals with eating pathology. A range of statistical models exist to handle these types of frequency distributions, but little empirical evidence exists to guide the appropriate choice of statistical model.

Method—Monte Carlo simulations were used to investigate the utility of semi-continuous models relative to continuous models in various situations relevant to binge eating treatment studies.

Results—Semi-continuous models yielded more accurate estimates of the population, while continuous models were higher powered when higher levels of missing data were present.

Discussion—The present findings generally support the use of semi-continuous models applied to binge eating data, with total sample sizes of roughly 200 being adequately powered to detect moderate treatment effects. However, models with a significant amount of missing data yielded more favorable power estimates for continuous models.

Binge eating is the core eating disturbance among those with bulimia nervosa (BN) and binge eating disorder (BED). Frequency of binge eating episodes is traditionally the primary outcome reported for treatment interventions targeting these populations. Meta-analyses of binge eating treatment studies report large effect sizes,¹ with full remission rates—denoting zero binges at time of measurement—of 48.7% and 28.5% for treatment and placebo conditions, respectively.² In addition, participants with a rapid response to treatment are more likely to achieve binge eating remission at end of treatment.^{3–7} A rapid response is typically defined as a >65% reduction in binge eating frequency by the fourth week of treatment,⁵ such that the distribution of binge eating frequency becomes highly positively skewed (see Figure 1). Therefore, binge eating data are often characterized by a preponderance of 0's—indicating those participants in full remission—at even early time points. The present investigation sought to identify appropriate statistical models that can be applied to eating disorder outcomes measured on a continuous scale, as opposed to a discrete (i.e., integer) scale, characterized by an excess of 0's. These outcomes might include, for

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example, average number of purge episodes or instances of laxative misuse, though the main focus here is the analytical approach to binge eating.

In general, past longitudinal research examining binge eating, and other continuous measures (e.g., purge episodes), as a primary outcome has utilized latent growth curve models with binge eating episodes at individual time points treated as continuous outcome variables. Growth curve models function within a latent variable modeling framework to estimate an unobserved growth factor over time (i.e., slope). The primary outcomes of interest for this type of analysis are the results of the regression of covariates, for example treatment assignment, on the growth factor. One of the assumptions of this statistical technique is normally distributed residuals at individual time points, independent of covariates,⁸ the violation of which can cause unduly biased results.⁹ As previously stated, the distribution of binge eating frequency in published treatment studies is positively skewed rather than normally distributed. It should be noted that a skewed outcome is not necessarily indicative of non-normally distributed residuals—the distribution of residuals when accounting for any number of covariates may be normal. However, given high remission rates in even placebo treatment conditions, and models that include treatment assignment as the only covariate, it is highly likely that the distribution of residuals will also be skewed. In addition, though the growth factor indicative of change over time may be normally distributed, the normality assumptions are not pertinent to this aspect of the model. Point estimates for biased results produced by a linear growth model treating binge eating as a continuous outcome may inaccurately estimate change in treatment symptoms over time between treatment conditions due to non-normally distributed residuals. In addition, unnecessarily inflated residuals due to poor model fit can lead to larger standard errors, resulting in wider confidence intervals and an underpowered model.

Practically speaking, the noted problems of a continuous model for binge eating data may include inaccurate conclusions regarding normative early change indicators, and over or under estimated treatment differences at the end of treatment. As recommendations about best practices are often built on the size of these treatment effects, accurate estimation of symptom change has broad public health significance. Thus, it is important to consider other, less problematic, approaches to analyzing and modeling binge eating data. One approach to consider is a semi-continuous (i.e., two-part) model that can account for non-normally distributed residuals by combining continuous and binary outcomes.¹⁰

A semi-continuous model can be viewed as the result of two processes predicting a binary or continuous outcome. The process pertaining to the binary outcome functions to compare 0 and non-0 values, while the results of the continuous outcome focus exclusively on non-0 data to determine the degree to which the behavior is present. In the context of binge eating data, this would allow the researcher to examine the possible differential role of covariates (e.g., education levels, age, etc.) for those who reach full remission and those that continue to binge on a nominal level, as well as how covariates relate to the number of binges for those still engaging in the behavior. The researcher is able to analyze the distinct role of covariates as a semi-continuous model estimates two separate growth factors for the binary and continuous process. The extent to which the binary and continuous processes of a semi-continuous model are distinct depends on the research design and theoretical reasoning, not

the choice of the model. That is, if a score 0 is due to limited sensitivity of the measurement techniques, for example with hormone analyses, then interpretation of results will be different from binge eating data when a score of 0 carries nominal significance.

Although sample selection models—such as Heckman's selection model¹¹—may be appropriate for truncated or censored dependent variables, these models are problematic when analyzing binge eating data as they are designed to deal with cases when a score of 0 acts as proxy for negative or missing values. That is, a semi-continuous model is preferred over sample selection models, as the latter are difficult to interpret when 0's represent real outcomes,¹² as in the present case where 0's represent full remission. A logarithmic transformation that attempts to stabilize the variance might also be applied. However, for a continuous model these transformations require adding an artificial amount, usually 1, to all measurements in order to account for 0's in the data. This results in unnecessary bias in mean estimates and estimated root mean-squared error that is particularly pronounced for highly skewed count data.¹³

Another option would be to use growth models designed to deal with both count outcomes and excess 0's. More specifically, zero-inflated Poisson (ZIP)¹⁴, or zero-inflated negative binomial models (ZINB)¹⁵ might be utilized. Both function like semi-continuous models in that the outcome is used to estimate two growth models. For ZIP and ZINB the first model includes the full spectrum of scores, including zero values, based on either a Poisson(λ) or negative binomial distribution. The second model uses a logit model to examine the probability of assuming any value except 0. These models were compared only at the population level, discussed further below, as the primary focus of the present paper was the appropriate statistical approach to binge eating outcomes on a continuous scale. That is, ZIP and ZINB models are designed to deal with solely ordinal values, while the present study sought to examine the utility of approaches able to model data that reflect average binge eating episodes over a period of time. For example, if the primary outcome is average binge eating per week over the past 28 days, a data point of 3.5 binge eating episodes could not be entered into count models. This outcome might be obtained if the researcher averages weekly responses over a number of weeks to represent a more stable measure of treatment effect. Conversely, it might be that a participant reasonably feels that a non-integer value best captures the average level of bingeing over some period of time. While data on an ordinal scale is certainly prevalent in eating disorders research, the question of appropriate model choice is a different one, and beyond the scope of the present investigation. In addition, O'Hara and Kotze¹³ have already provided an initial Monte Carlo investigation for count data, with recommendations to apply negative binomial or Poisson models.

The present study sought to examine the advantages of a semi-continuous model relative to a continuous linear growth curve model in analyzing binge eating data on a continuous scale, with the aim of providing investigators a set of general guidelines to reference when considering both study design and analytic approach to binge eating data. Using Monte Carlo simulation, the performance of these models was examined within different contexts (e.g., different sample sizes, missing data, etc.) relevant to binge eating treatment studies. In all situations, we hypothesized the semi-continuous model would provide more comprehensive and accurate findings. These results were expected given that continuous

models may produce inaccurate point estimates, higher levels of Type II error, and less precision in results, as evidenced by larger standard errors. Though the simulations were structured with the characteristics of binge eating data in mind, the present findings may also be used to inform statistical approaches when analyzing other forms of positively skewed data. Within the eating disorder field this will be particularly relevant when considering statistical approaches for other continuous outcomes, including number of purge episodes or excessive exercise.

Method

Generating Population Values

In order to examine the ability of each model to provide accurate estimates of population parameters, data sets with total sample sizes of 100,000 were first generated using the Monte Carlo function in Mplus.¹⁶ Population starting values were based on available information in the binge eating literature, and were set to vary only in terms of generated effect size as measured by Cohen's *d*. That is, the effect of treatment on slope (i.e., change in bingeing over time)—computed as the difference in means for the two artificial treatment conditions divided by the standard deviation of the slope—was manipulated to reflect small, medium, and large effect sizes following standard convention.¹⁷ Assumptions relevant to Cohen's *d*, namely normally distributed residuals and homogeneity of variance, are untenable in the context of binge eating data. Data were simulated to reflect values of Cohen's *d* to allow for more direct comparison with prior findings, however; non-parametric effect sizes are also reported below, and should be preferred when assumptions are violated. For all effect sizes, covariance between the slope and baseline level of binge eating episodes (i.e., intercept) was free to be estimated at .5. Additionally, covariance between the intercept and treatment assignment was fixed at 0 to reflect true randomization.

Mean level of binge eating across treatment conditions was set to be 8 objective binge episodes over the past 28 days at baseline. This reflects DSM-IV¹⁸ criteria for binge eating frequency over the past month in BED and BN, as commonly assessed for in treatment studies using measures such as the Eating Disorder Examination, and allows for comparison of the resulting simulated treatment effects of this investigation to those of recently published studies. Data were simulated at seven discrete time points to reflect the majority of change up through the fourth point, followed by a steady decrease in binge eating behavior for points five and six, and almost no change through point 7. Time was then treated as a fixed variable at points 0, 1, 2, 4, 6, 8, and 12 to reflect an 8-week treatment study with one follow-up assessment.

The data sets, intended to represent populations of interest, were analyzed using statistical techniques designed to deal with excess 0's; latent growth curve models that treat binge eating frequency as a continuous or specifically count outcome, using maximum likelihood estimators robust to standard errors were estimated. More specifically, ZIP, ZINB, semi-continuous (see Supplementary Materials), and continuous models were assessed using three model fit information criteria: the Akaike Information Criterion (AIC¹⁹), the Bayesian Information Criterion (BIC²⁰), and the Sample Size Adjusted Bayesian Information Criterion (aBIC²¹). For ZIP and ZINB models, the simulated data points were rounded to the

nearest integer value. Among the count models, ZIP models provided better fit at large effect sizes, while fit indices were smaller for ZINB for small and medium effects (Table 1). Irrespective of effect size, the semi-continuous model provided a better fit of the data relative to continuous models, as indicated by relatively smaller information criteria values. While model fit indices on their own are not necessarily indicative of a suitable statistical approach, as semi-continuous models are also theoretically appropriate for binge eating data we took this to be indicative of better model fit. Estimated parameters from the semi-continuous population data were used as starting values in all subsequent models to be tested. Separate starting values were used for log-transformed data sets (discussed below). In addition to the type of model run, four factors were manipulated in order to examine the suitability of continuous and semi-continuous models within different methodological contexts. For each scenario considered below, 10,000 replications (i.e., data sets) were generated in order to ensure stability of reported results.

Sample Size

Review of the current binge eating literature suggests an average total sample size in treatment studies to be between 60 and 80 participants. However, total sample sizes can range from below 40²² to close to 400.²³ Replications were designed to reflect this variability, with generated total sample sizes of 40, 60, 80, 100, 150, 200, and 500. Samples below 40 were not analyzed as the majority of replications failed to converge for both semi-continuous and continuous models.

Missing Data

Missing data are ubiquitous for any treatment study. Four levels of missing data were generated at 10%, 20%, 25%, and 40%. Data sets containing no missing data were also generated as a point of comparison. The mechanism for missing data was established as missing at random (MAR²⁴). Missing data that is MAR is assumed to be independent from the underlying values of missing data. That is, the model assumes attrition is unrelated to number of binge episodes at time of dropout. However, MAR data are associated with an observed variable, in this case treatment condition. Missing data was not treated as monotonic; simulations were not generated under the assumption that participants with earlier missing data were necessarily missing at all subsequent time points. A linear increase in missing data was specified across the fixed time points with no missing data at baseline (i.e., time 0).

Effect Size

Mean differences between treatments are primarily a function of the two groups being compared. Put another way, if a highly effective intervention is compared to a placebo group, the effect size is likely to be larger than if two effective treatments are compared. It is unsurprising then that effect sizes vary greatly within the literature. With this in mind, data were generated to reflect small, medium and large effect sizes using established guidelines.¹⁵ The standard effect sizes in the population were specifically .23, .52, and .81.

As noted earlier, assumptions relevant to the standard effect size were not met in the simulated data. As a measure of nonparametric effect size we used area under the curve

(AUC)—also known as the probability of superiority—to test the extent to which a randomly sampled member from one treatment group binge eats less than a randomly sampled member from the other treatment group.²⁵ We specifically used a robust measure of AUC that assumes neither a normal distribution nor homogeneity of variance.²⁶⁻²⁷ With a linear transformation applied to place the effect size value on an interval [0, 1], estimates were specifically .04, .08, and .12. Although these estimates may appear small, this is due in large part to the nature of the effect size estimate. That is, for AUC effect sizes the probability that one treatment will be particularly effective relative to another intervention is greatly reduced when both treatments result in high levels of full remission.

Logarithmic Transformation

As noted earlier, a log transformation that requires adding artificial values to the data (i.e., when 0's are present) may unduly bias results. However, when few or no 0's are present a log transformation may serve to stabilize variance without negatively affecting results.¹³ The variance estimates for the continuous outcome in a semi-continuous model may then benefit from a log transformation that stabilizes the variance. To test this hypothesis, both semi-continuous and continuous models were also analyzed with an applied log base 10 transformation. For the log-transformed continuous model a value of .001 was added to scores of 0.

Primary Outcomes

Nine primary criteria were used to assess the suitability of each model within the contexts described above. Model fit was evaluated using AIC, BIC, and aBIC. As semi-continuous models are not nested within continuous models these values should only be compared between log-transformed and untransformed models of the same type, with smaller values indicating a better fit. Of particular interest was the extent to which each model biased estimates of the effect of treatment on change in binge eating over time for the continuous outcome. Parameter bias was computed as the difference between the parameter estimate average across all replications, and the population value, divided by the population value.²⁸ Standard error bias for the effect of treatment on slope was calculated in the same way as parameter bias. Coverage—the proportion of replications for which the 95% confidence interval contained the population value—provides additional information relevant to the accuracy of the estimated parameter value. Root mean-squared error, an indicator of bias, is calculated as the variance of estimates across replications, plus bias squared. Percent convergence reflects the percentage of the 10,000 replications that converged within 500 iterations. Finally, estimates of power were computed as the proportion of replications that led to rejection of the null hypothesis that the effect of treatment on change was 0 at the .05 level, using a two-tailed test. As the population effect size was always different from 0, larger values are indicative of a higher-powered model that yields lower levels of Type II error.

Results

Tables 2-7 present primary outcomes, split between levels of effect sizes, and whether a log transformation was applied. The information criteria for log-transformed data were

significantly lower in all cases. Both model types had high convergence rates, >92%, for all effect sizes, and total sample sizes greater than 40. For sample sizes of 40, a lower percentage of semi-continuous models converged after 500 iterations, particularly at higher levels of missing data. Findings for the remaining outcomes are considered below.

Parameter Bias, RMSE, and Coverage

Continuous models applied to untransformed data produced highly biased, underestimated estimates of treatment effect. While semi-continuous models also underestimated the parameter, the degree of bias was markedly lower. When data were log-transformed the continuous model still produced highly biased estimates that overestimated treatment effect. As with untransformed data, semi-continuous models underestimated the value of the parameter, and produced estimates that were less biased than continuous models. Thus, semi-continuous models were more likely to produce estimates of treatment effect that closely approximated the population value.

For untransformed data, standard error bias for continuous and semi-continuous models was approximately equal, though semi-continuous models yielded less biased results overall. In select cases—for medium and large effect sizes with samples larger than 100—continuous models produced less biased estimates of standard error. In all contexts, continuous models applied to log-transformed data produced less biased estimates of standard error compared to semi-continuous models.

Continuous models applied to untransformed data at small effect sizes yielded lower RMSE values. For medium and large effect sizes, semi-continuous models generally produced smaller levels of RMSE, particularly at larger sample sizes and lower levels of missing data. In all cases, semi-continuous models applied to log-transformed data yielded lower levels of RMSE relative to continuous models.

Overall, the proportion of 95% confidence intervals that captured the population value was higher for semi-continuous models applied to both log-transformed and untransformed data. The difference was particularly pronounced with untransformed data, as coverage for continuous models was, on average, only 20%, compared to 91% coverage for semi-continuous models. Mixed results for log-transformed data indicated that coverage was generally higher when semi-continuous models were used, though continuous models tended to perform better at smaller sample sizes of 40 and 60.

Power

Semi-continuous models applied to untransformed data were higher powered than continuous models in almost all cases; at higher levels of missing data, with small effect sizes and samples greater than 80, continuous models achieved higher relative power. Conversely, semi-continuous models were generally underpowered relative to continuous models when data were log-transformed. Semi-continuous models performed better in the context of smaller sample and effect sizes, as well as at lower levels of missing data. The difference between the models was heightened by the increased ability of continuous models to detect an effect at higher levels of missing data.

Discussion

The present study provides practical guidelines for analyzing binge eating data. In choosing a model, sample size, expected effect size, and level of missingness in the data are all clearly important factors to consider. Beyond these factors, model choice will also be informed by the particular goals of the investigation. That is, if the difference between the treatments is already well established, and the primary goal is to determine the *degree* to which they are different, then a semi-continuous model is likely to provide the closest approximation of the true effect.

The level of Type II error for both models was considerably higher in most contexts than the generally accepted threshold 20%, even when the effect size was large. For example, the power to detect a large effect with a sample size of 60, and no missing data, was 23.4% and 25.5% for semi-continuous and continuous models, respectively. In the raw data, averaged across replications, the large effect size looked like an overall difference of .67 binge eating episodes between conditions at end of treatment, which may seem like a minor difference, but is actually of clinical significance. A difference of .67 binge eating episodes may affect whether or not an individual continues to meet diagnostic criteria for BED, and if so, the individual's level of eating disorder severity according to the recent DSM-5²⁹. For those still engaging in binge eating at the end of treatment there was a .52 difference in number of binge episodes, and more importantly 15% more participants reached full remission in the more effective treatment. Limited power to detect a treatment difference was undoubtedly due in large part to the number of fixed time points estimated for both models. The greater number of observations may increase power to detect significant slope effects (e.g., change in binge episodes over time)³⁰, but reduce the power to detect end-of-treatment differences. Researchers might then seek to employ a statistical approach that limits the comparison to only beginning and end of treatment levels of binge eating in order to reduce the number of parameters, and increase power. If sample size is a limiting factor then this may like seem the most sensible option, especially in light of present findings indicating samples of 200 or greater may be necessary to achieve 80% power to detect an effect. However, beginning versus end of treatment approaches should be viewed with some scrutiny, as these approaches fail to consider the trajectory of change over time. That is, binge eating is unlikely to steadily decrease from start of treatment, with no instances of relapse. When the trajectory of change is then limited to two time points—start and end of treatment—the reported findings potentially capitalize on what would be considered a ‘good’ week for some participants, thereby failing to capture an oscillating pattern of behavior.

If change in binge eating over multiple time points is relevant to the investigation, and in most cases we imagine it would be, then the choice to use both a semi-continuous and continuous model is perhaps the best option, particularly for smaller sample sizes and higher levels of missing data. After log transforming data, semi-continuous models estimated treatment effect with less bias, but at the cost of less power to detect an effect. In light of these findings a combination of continuous and semi-continuous models might be applied to reach qualitative and quantitative conclusions regarding treatment effect, respectively. This approach would involve first applying a continuous model, given lower levels of Type II error, to determine whether or not the treatments are differentially effective. Subsequently, a

semi-continuous would be applied to determine the *degree* to which the two treatments are different. Such an approach is both higher powered and less likely to bias parameter estimates. Moreover, the combination of both models would provide more comprehensive results allowing for nuanced conclusions.

The present study is one of the first to use Monte Carlo simulation to investigate the utility of semi-continuous and continuous models in analyzing data from studies of binge eating treatment. Results suggest that combining a continuous model with a semi-continuous model may allow researchers to reach more accurate conclusions regarding the effectiveness of a given treatment. Semi-continuous models are also theoretically appealing as the separate growth factors estimated by a semi-continuous model may provide novel, clinically relevant insights. For example, the researcher might find that one personality trait predicts full remission, while another trait only relates to the degree of binge eating for those that continue to engage in the behavior. Results also suggest that past research regarding binge eating treatment should be interpreted with caution, particularly if no attempts were made to address the large number of ties at 0. However, the present study is not without its own limitations, which include the performance of different models in the context of designs and factors not considered. Nevertheless, the present study offers important and practical guidelines for choosing a statistical approach to analyzing binge eating data. One limitation of the semi-continuous model is that patients will likely be fully symptomatic at baseline assessments (i.e., no 0's in the data at that time point). Given the level of disparity between findings for the different models, an important topic for future research will be identifying the best statistical approach for different research aims. In addition, future simulation studies should consider a range of different modeling approaches, including further examination of count models, or survival curves modeling time to full remission.³¹ As an overview of model performance at typical levels of the more critical factors, the presented results should be used to aid in initial considerations of study design, and to inform analytic approaches.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

Representation of how data become skewed early on in binge eating data. (A) Figure depicts continuous growth curve model for hypothetical data based on values reported in the literature. Clusters of data at 0 binge episodes at any given time point evidence a positively skewed distribution. (B) At week 4 the distribution is already highly positively skewed due to a preponderance of 0's.

Table 1**Fit Indices for Count Models**

Model	AIC	BIC	aBIC
Small Effect			
ZIP	220638	220710	220678
ZINB	223207	223330	223276
Medium Effect			
ZIP	216520	216592	216560
ZINB	215768	215891	215837
Large Effect			
ZIP	209651	209723	209691
ZINB	209658	209781	209727

Note. ZIP = zero-inflated Poisson; ZINB = zero-inflated negative binomial.

Table 2

Untransformed Models Estimating Small Effect

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
40	0	SEMI	989	1018	965	-0.186	-0.154	0.866	0.146
		CONT	1167	1189	1149	-0.857	-0.170	0.557	0.063
	10	SEMI	973	1002	949	-0.101	-0.142	0.870	0.143
		CONT	1142	1164	1123	-0.778	-0.178	0.605	0.073
	20	SEMI	959	988	935	-0.002	-0.133	0.867	0.146
		CONT	1118	1140	1099	-0.703	-0.169	0.647	0.081
	25	SEMI	950	978	925	0.039	-0.143	0.866	0.150
		CONT	1104	1125	1085	-0.657	-0.174	0.668	0.087
60	0	SEMI	1469	1505	1452	-0.178	-0.119	0.898	0.121
		CONT	1753	1780	1740	-0.856	-0.113	0.515	0.065
	10	SEMI	1444	1480	1426	-0.136	-0.121	0.896	0.124
		CONT	1715	1743	1702	-0.777	-0.108	0.580	0.075
	20	SEMI	1422	1457	1404	-0.072	-0.119	0.892	0.127
		CONT	1679	1707	1666	-0.690	-0.112	0.635	0.088
	25	SEMI	1406	1442	1389	-0.051	-0.115	0.892	0.127
		CONT	1657	1685	1644	-0.647	-0.111	0.669	0.098
80	0	SEMI	1953	1993	1940	-0.155	-0.071	0.918	0.106
		CONT	2338	2369	2328	-0.849	-0.085	0.460	0.063
	10	SEMI	1919	1960	1906	-0.123	-0.075	0.916	0.107
		CONT	2288	2319	2278	-0.769	-0.086	0.532	0.077
	20	SEMI	1888	1929	1875	-0.076	-0.079	0.915	0.112
		CONT	2240	2271	2230	-0.684	-0.093	0.613	0.097
	25	SEMI	1868	1909	1855	-0.064	-0.078	0.914	0.113
		CONT	2211	2242	2201	-0.637	-0.085	0.650	0.107
100	0	SEMI	2438	2482	2428	-0.157	-0.059	0.925	0.103
		CONT	2924	2958	2917	-0.850	-0.065	0.408	0.066
	10	SEMI	2396	2440	2386	-0.126	-0.061	0.923	0.106
		CONT	2861	2895	2854	-0.770	-0.067	0.492	0.082

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
150	20	SEMI	2357	2401	2348	-0.079	-0.053	0.923	0.110
		CONT	2801	2835	2794	-0.686	-0.066	0.578	0.101
	25	SEMI	2332	2376	2322	-0.072	-0.059	0.925	0.109
		CONT	2765	2799	2757	-0.638	-0.066	0.624	0.118
	0	SEMI	3649	3700	3646	-0.139	-0.035	0.931	0.110
		CONT	4387	4426	4385	-0.847	-0.033	0.290	0.070
200	10	SEMI	3586	3637	3583	-0.111	-0.037	0.933	0.112
		CONT	4292	4331	4290	-0.765	-0.035	0.388	0.096
	20	SEMI	3528	3579	3525	-0.066	-0.038	0.934	0.117
		CONT	4202	4241	4200	-0.680	-0.034	0.496	0.125
	25	SEMI	3490	3541	3487	-0.059	-0.039	0.933	0.118
		CONT	4148	4187	4146	-0.632	-0.035	0.552	0.147
500	0	SEMI	4860	4916	4862	-0.136	-0.024	0.941	0.126
		CONT	5849	5892	5851	-0.847	-0.020	0.201	0.078
	10	SEMI	4776	4832	4778	-0.110	-0.026	0.939	0.129
		CONT	5723	5766	5724	-0.766	-0.020	0.302	0.112
	20	SEMI	4698	4754	4700	-0.065	-0.028	0.941	0.136
		CONT	5603	5646	5605	-0.680	-0.017	0.421	0.153
500	25	SEMI	4648	4704	4650	-0.059	-0.029	0.942	0.134
		CONT	5530	5573	5532	-0.633	-0.075	0.490	0.181
	0	SEMI	12125	12196	12142	-0.142	-0.014	0.943	0.220
		CONT	14624	14679	14637	-0.849	0.001	0.011	0.121
	10	SEMI	11915	11987	11933	-0.119	-0.014	0.943	0.223
		CONT	14308	14363	14322	-0.770	-0.003	0.038	0.216
500	20	SEMI	11721	11793	11739	-0.074	-0.014	0.945	0.235
		CONT	14009	14064	14023	-0.685	-0.001	0.110	0.331
	25	SEMI	11595	11666	11612	-0.069	-0.015	0.945	0.233
		CONT	13827	13882	13841	-0.638	-0.001	0.176	0.398

Note:

* SEMI = Semi-continuous Model;

** CONT = Continuous Model.

Table 3

Log-transformed Models Estimating Small Effect

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
40	0	SEMI	334	363	310	-0.179	-0.118	0.885	0.117
		CONT	872	894	853	0.284	-0.046	0.935	0.074
	10	SEMI	327	355	302	-0.125	-0.096	0.891	0.116
		CONT	850	872	831	0.648	-0.047	0.933	0.080
	20	SEMI	319	348	295	-0.100	-0.108	0.891	0.111
		CONT	828	850	810	1.015	-0.049	0.930	0.087
	25	SEMI	315	343	290	-0.080	-0.101	0.893	0.112
		CONT	816	838	797	1.199	-0.051	0.929	0.092
60	0	SEMI	504	540	486	-0.204	-0.091	0.912	0.100
		CONT	1311	1338	1297	0.253	-0.029	0.938	0.075
	10	SEMI	493	528	475	-0.223	-0.090	0.911	0.098
		CONT	1277	1304	1264	0.610	-0.028	0.936	0.082
	20	SEMI	482	517	464	-0.238	-0.086	0.910	0.095
		CONT	1245	1272	1231	0.978	-0.027	0.934	0.093
	25	SEMI	475	511	457	-0.258	-0.084	0.909	0.093
		CONT	1226	1253	1213	1.165	-0.027	0.931	0.099
80	0	SEMI	674	715	661	-0.180	-0.054	0.931	0.086
		CONT	1748	1779	1738	0.280	-0.011	0.947	0.074
	10	SEMI	659	699	646	-0.218	-0.054	0.929	0.082
		CONT	1703	1734	1693	0.630	-0.007	0.943	0.087
	20	SEMI	644	685	631	-0.253	-0.050	0.925	0.081
		CONT	4148	4191	4195	0.965	-0.010	0.922	0.175
	25	SEMI	635	676	622	-0.276	-0.055	0.926	0.079
		CONT	1636	1667	1626	1.171	-0.009	0.933	0.110
100	0	SEMI	845	889	835	-0.196	-0.052	0.935	0.085
		CONT	2185	2219	2177	0.269	-0.020	0.945	0.077
	10	SEMI	826	870	816	-0.239	-0.056	0.929	0.082
		CONT	2129	2163	2122	0.615	-0.018	0.940	0.094

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
150	20	SEMI	807	852	798	-0.278	-0.056	0.929	0.081
		CONT	2076	2109	2068	0.968	-0.019	0.936	0.111
	25	SEMI	796	841	787	-0.313	-0.055	0.928	0.079
		CONT	2044	2078	2037	1.153	-0.021	0.927	0.120
	0	SEMI	1272	1323	1269	-0.190	-0.026	0.939	0.084
		CONT	3275	3314	3273	0.283	-0.002	0.948	0.093
200	10	SEMI	1243	1294	1240	-0.240	-0.028	0.938	0.082
		CONT	3192	3231	3190	0.629	-0.001	0.942	0.115
	20	SEMI	1216	1267	1213	-0.285	-0.027	0.936	0.076
		CONT	3112	3151	3110	0.979	-0.002	0.930	0.143
	25	SEMI	1199	1250	1196	-0.321	-0.029	0.935	0.075
		CONT	3065	3104	3063	1.165	-0.003	0.920	0.156
200	0	SEMI	1698	1754	1701	-0.183	-0.019	0.944	0.093
		CONT	4366	4409	4368	0.275	-0.009	0.944	0.106
	10	SEMI	1660	1716	1662	-0.234	-0.021	0.943	0.088
		CONT	4254	4297	4256	0.616	-0.009	0.936	0.138
	20	SEMI	1624	1680	1626	-0.279	-0.019	0.942	0.082
		CONT	4148	4191	4199	0.965	-0.010	0.922	0.175
500	25	SEMI	1602	1658	1604	-0.318	-0.020	0.942	0.079
		CONT	4086	4128	4087	1.150	-0.011	0.908	0.194
	0	SEMI	4264	4336	4282	-0.188	-0.014	0.943	0.143
		CONT	10906	10961	10919	0.266	0.006	0.947	0.190
	10	SEMI	4169	4240	4186	-0.241	-0.016	0.938	0.130
		CONT	10628	10682	10641	0.601	0.006	0.924	0.268
500	20	SEMI	4077	4149	4095	-0.289	-0.015	0.933	0.118
		CONT	10362	10417	10376	0.951	0.007	0.883	0.358
	25	SEMI	4022	4093	4039	-0.328	-0.015	0.931	0.111
		CONT	10206	10260	10219	1.134	-0.033	0.853	0.403

Table 4

Untransformed Models Estimating Medium Effect

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
40	0	SEMI	970	998	945	-0.082	-0.163	0.859	0.201
		CONT	1158	1180	1139	-0.872	-0.190	0.169	0.071
	10	SEMI	955	984	931	-0.048	-0.147	0.863	0.197
		CONT	1134	1156	1115	-0.837	-0.200	0.206	0.086
	20	SEMI	942	971	918	-0.001	-0.139	0.865	0.200
		CONT	1111	1133	1092	-0.801	-0.194	0.250	0.100
	25	SEMI	934	962	909	0.019	-0.140	0.866	0.198
		CONT	1097	1119	1078	-0.779	-0.194	0.278	0.108
60	0	SEMI	1438	1473	1420	-0.092	-0.129	0.892	0.210
		CONT	1741	1769	1728	-0.869	-0.132	0.099	0.086
	10	SEMI	1415	1451	1397	-0.077	-0.131	0.890	0.208
		CONT	1705	1732	1691	-0.832	-0.141	0.135	0.109
	20	SEMI	1394	1430	1377	-0.051	-0.130	0.887	0.206
		CONT	1670	1697	1656	-0.794	-0.139	0.181	0.130
	25	SEMI	1381	1416	1363	-0.041	-0.126	0.889	0.208
		CONT	1649	1676	1635	-0.772	-0.136	0.210	0.142
80	0	SEMI	1910	1950	1896	-0.084	-0.074	0.911	0.222
		CONT	2324	2355	2314	-0.865	-0.104	0.059	0.099
	10	SEMI	1879	1920	1866	-0.072	-0.077	0.911	0.222
		CONT	2275	2306	2265	-0.828	-0.105	0.088	0.125
	20	SEMI	1851	1892	1838	-0.049	-0.078	0.910	0.221
		CONT	2229	2260	2219	-0.788	-0.115	0.132	0.158
	25	SEMI	1833	1873	1820	-0.046	-0.078	0.911	0.219
		CONT	2200	2231	2190	-0.766	-0.109	0.160	0.174
100	0	SEMI	2384	2428	2374	-0.084	-0.064	0.923	0.248
		CONT	2907	2941	2900	-0.865	-0.082	0.036	0.115
	10	SEMI	2345	2390	2336	-0.071	-0.062	0.922	0.246
		CONT	2846	2880	2838	-0.827	-0.085	0.060	0.147

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
150	20	SEMI	2310	2355	2301	-0.050	-0.067	0.923	0.248
		CONT	2788	2821	2780	-0.787	-0.088	0.097	0.182
	25	SEMI	2287	2331	2278	-0.047	-0.066	0.922	0.244
		CONT	2752	2786	2745	-0.765	-0.086	0.120	0.200
	0	SEMI	3567	3618	3564	-0.075	-0.041	0.932	0.322
		CONT	4363	4402	4361	-0.864	-0.043	0.010	0.148
	10	SEMI	3510	3561	3507	-0.063	-0.042	0.931	0.321
		CONT	4271	4310	4269	-0.825	-0.049	0.021	0.199
	20	SEMI	3457	3509	3455	-0.042	-0.044	0.933	0.323
		CONT	4183	4223	4181	-0.784	-0.049	0.041	0.253
	25	SEMI	3423	3474	3420	-0.040	-0.046	0.934	0.320
		CONT	4130	4169	4128	-0.762	-0.047	0.057	0.283
200	0	SEMI	4751	4807	4753	-0.072	-0.028	0.940	0.408
		CONT	5818	5861	5820	-0.864	-0.025	0.003	0.190
	10	SEMI	4674	4730	4676	-0.060	-0.029	0.939	0.406
		CONT	5695	5738	5697	-0.825	-0.026	0.007	0.252
	20	SEMI	4605	4661	4607	-0.040	-0.033	0.938	0.409
		CONT	5579	5622	5581	-0.785	-0.026	0.017	0.325
	25	SEMI	4558	4614	4560	-0.039	-0.034	0.938	0.404
		CONT	5508	5551	5510	-0.762	-0.024	0.025	0.365
	0	SEMI	11853	11925	11871	-0.075	-0.021	0.939	0.766
		CONT	14550	14605	14564	-0.864	-0.001	0.000	0.404
	10	SEMI	11662	11734	11680	-0.065	-0.021	0.940	0.767
		CONT	14244	14299	14257	-0.828	-0.004	0.000	0.561
500	20	SEMI	11488	11559	11505	-0.045	-0.021	0.943	0.771
		CONT	13953	14007	13966	-0.788	-0.005	0.000	0.690
	25	SEMI	11371	11443	11389	-0.043	-0.023	0.942	0.764
		CONT	13775	13829	13788	-0.765	0.000	0.002	0.744

Table 5

Log-transformed Models Estimating Medium Effect

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
40	0	SEMI	333	362	308	-0.038	-0.120	0.883	0.152
		CONT	877	898	858	0.327	-0.051	0.932	0.117
	10	SEMI	326	354	301	-0.037	-0.108	0.888	0.148
		CONT	854	876	836	0.518	-0.051	0.928	0.129
	20	SEMI	318	347	294	-0.036	-0.093	0.889	0.143
		CONT	833	855	814	0.713	-0.050	0.926	0.143
	25	SEMI	314	343	290	-0.042	-0.087	0.889	0.138
		CONT	820	842	802	0.815	-0.050	0.922	0.150
60	0	SEMI	502	538	484	-0.081	-0.100	0.911	0.148
		CONT	1317	1344	1303	0.303	-0.030	0.937	0.138
	10	SEMI	491	527	473	-0.096	-0.099	0.907	0.147
		CONT	1283	1310	1270	0.487	-0.030	0.933	0.158
	20	SEMI	484	517	463	-0.105	-0.091	0.908	0.143
		CONT	1251	1279	1238	0.679	-0.028	0.929	0.180
	25	SEMI	475	510	457	-0.122	-0.088	0.908	0.137
		CONT	1232	1260	1219	0.779	-0.028	0.924	0.193
80	0	SEMI	672	712	658	-0.072	-0.062	0.927	0.148
		CONT	1755	1786	1745	0.306	-0.012	0.944	0.165
	10	SEMI	657	698	644	-0.098	-0.063	0.924	0.143
		CONT	1711	1742	1701	0.488	-0.008	0.940	0.193
	20	SEMI	644	684	631	-0.115	-0.066	0.920	0.139
		CONT	1669	1700	1659	0.676	-0.010	0.930	0.226
	25	SEMI	635	676	622	-0.130	-0.063	0.921	0.135
		CONT	1644	1675	1634	0.777	-0.009	0.922	0.242
100	0	SEMI	841	886	832	-0.081	-0.062	0.928	0.169
		CONT	2194	2228	2187	0.297	-0.017	0.943	0.200
	10	SEMI	823	868	814	-0.105	-0.064	0.927	0.163
		CONT	2138	2172	2131	0.478	-0.017	0.933	0.236

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
150	20	SEMI	807	851	797	-0.125	-0.062	0.925	0.156
		CONT	2085	2119	2078	0.665	-0.018	0.921	0.272
	25	SEMI	796	840	786	-0.141	-0.061	0.923	0.152
		CONT	2054	2088	2047	0.764	-0.019	0.913	0.292
	0	SEMI	1266	1317	1263	-0.080	-0.036	0.939	0.208
		CONT	3289	3328	3287	0.299	0.001	0.942	0.274
	10	SEMI	1238	1290	1236	-0.106	-0.038	0.936	0.194
		CONT	3205	3244	3203	0.478	0.002	0.929	0.332
	20	SEMI	1213	1264	1210	-0.128	-0.037	0.937	0.182
		CONT	3126	3165	3124	0.665	0.002	0.909	0.383
	25	SEMI	1197	1248	1194	-0.148	-0.039	0.937	0.174
		CONT	3079	3118	3077	0.764	0.000	0.893	0.414
200	0	SEMI	1690	1746	1692	-0.074	-0.025	0.942	0.256
		CONT	4384	4426	4385	0.295	-0.003	0.936	0.354
	10	SEMI	1654	1710	1656	-0.102	-0.026	0.941	0.240
		CONT	4272	4315	4274	0.473	-0.005	0.918	0.425
	20	SEMI	1620	1676	1622	-0.127	-0.028	0.939	0.226
		CONT	4167	4210	4168	0.659	-0.006	0.886	0.492
	25	SEMI	1599	1655	1601	-0.146	-0.028	0.939	0.214
		CONT	4104	4147	4106	0.758	-0.007	0.870	0.525
	0	SEMI	4241	4312	4259	-0.084	-0.024	0.938	0.522
		CONT	10949	11004	10963	0.284	0.005	0.920	0.709
	10	SEMI	4150	4222	4168	-0.113	-0.026	0.934	0.490
		CONT	10672	10727	10685	0.459	0.004	0.865	0.798
500	20	SEMI	4065	4137	4083	-0.137	-0.902	0.933	0.461
		CONT	10408	10462	10421	0.644	0.003	0.783	0.867
	25	SEMI	4012	4083	4029	-0.158	-0.024	0.927	0.442
		CONT	10251	10306	10265	0.742	0.004	0.737	0.897

Table 6

Untransformed Models Estimating Large Effect

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
40	0	SEMI	949	977	924	-0.029	-0.161	0.854	0.291
		CONT	881	903	862	0.308	-0.055	0.937	0.186
	10	SEMI	936	964	911	-0.001	-0.155	0.862	0.291
		CONT	1125	1147	1107	-0.869	-0.223	0.063	0.099
	20	SEMI	924	953	900	0.028	-0.158	0.860	0.292
		CONT	1104	1126	1085	-0.845	-0.222	0.081	0.116
	25	SEMI	916	945	891	0.038	-0.148	0.859	0.291
		CONT	1090	1112	1071	-0.830	-0.219	0.094	0.127
60	0	SEMI	1403	1439	1385	-0.042	-0.131	0.885	0.347
		CONT	1729	1756	1715	-0.890	-0.161	0.021	0.112
	10	SEMI	1383	1418	1365	-0.032	-0.136	0.885	0.345
		CONT	1694	1721	1680	-0.864	-0.170	0.029	0.144
	20	SEMI	1365	1401	1347	-0.013	-0.141	0.882	0.339
		CONT	1661	1688	1647	-0.839	-0.165	0.043	0.174
	25	SEMI	1352	1388	1334	-0.007	-0.141	0.881	0.339
		CONT	1640	1667	1626	-0.824	-0.167	0.053	0.192
80	0	SEMI	1863	1903	1850	-0.040	-0.085	0.912	0.413
		CONT	2309	2340	2299	-0.887	-0.134	0.009	0.147
	10	SEMI	1836	1876	1822	-0.030	-0.090	0.910	0.402
		CONT	2262	2293	2252	-0.861	-0.138	0.014	0.186
	20	SEMI	1811	1851	1798	-0.016	-0.093	0.907	0.397
		CONT	2218	2249	2208	-0.834	-0.148	0.024	0.229
	25	SEMI	1794	1834	1781	-0.013	-0.095	0.907	0.394
		CONT	2190	2221	2180	-0.819	-0.146	0.032	0.255
100	0	SEMI	2325	2369	2316	-0.042	-0.065	0.921	0.478
		CONT	2889	2923	2882	-0.886	-0.109	0.003	0.176
	10	SEMI	2291	2335	2281	-0.034	-0.066	0.921	0.471
		CONT	2830	2864	2823	-0.861	-0.112	0.005	0.225

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
150	20	SEMI	2260	2304	2250	-0.020	-0.070	0.919	0.467
		CONT	2774	2808	2767	-0.833	-0.115	0.014	0.282
	25	SEMI	2239	2283	2229	-0.019	-0.071	0.920	0.459
		CONT	2740	2774	2733	-0.817	-0.115	0.018	0.309
	0	SEMI	3479	3530	3476	-0.036	-0.044	0.933	0.646
		CONT	4338	4377	4336	-0.885	-0.066	0.001	0.250
	10	SEMI	3428	3479	3425	-0.029	-0.047	0.932	0.641
		CONT	4250	4289	4248	-0.859	-0.073	0.002	0.327
	20	SEMI	3381	3432	3379	-0.015	-0.047	0.934	0.633
		CONT	4165	4205	4163	-0.831	-0.079	0.003	0.401
	25	SEMI	3350	3401	3347	-0.014	-0.051	0.932	0.624
		CONT	4113	4153	4111	-0.815	-0.078	0.005	0.436
200	0	SEMI	4633	4689	4635	-0.035	-0.029	0.939	0.776
		CONT	5787	5830	5789	-0.885	-0.037	0.001	0.322
	10	SEMI	4565	4621	4567	-0.028	-0.032	0.936	0.763
		CONT	5669	5712	5670	-0.859	-0.055	0.001	0.427
	20	SEMI	4503	4559	4505	-0.015	-0.034	0.935	0.756
		CONT	5556	5599	5558	-0.831	-0.056	0.002	0.517
	25	SEMI	4461	4517	4463	-0.015	-0.036	0.936	0.746
		CONT	5487	5530	5488	-0.816	-0.052	0.003	0.556
	0	SEMI	11559	11631	11577	-0.038	-0.019	0.939	0.989
		CONT	14478	14533	14491	-0.886	-0.007	0.000	0.690
	10	SEMI	11389	11461	11407	-0.032	-0.018	0.942	0.988
		CONT	14182	14236	14195	-0.861	-0.013	0.000	0.823
500	20	SEMI	11234	11306	11252	-0.019	-0.017	0.945	0.987
		CONT	13899	13954	13913	-0.834	-0.012	0.000	0.902
	25	SEMI	11129	11200	11146	-0.018	-0.020	0.944	0.986
		CONT	13725	13780	13739	-0.819	-0.021	0.000	0.929

Table 7

Log-transformed Models Estimating Large Effect

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
40	0	SEMI	330	359	306	0.054	-0.096	0.885	0.210
		CONT	1148	1170	1130	-0.893	-0.218	0.046	0.085
	10	SEMI	323	352	299	0.071	-0.096	0.890	0.205
		CONT	859	881	840	0.449	-0.049	0.936	0.203
	20	SEMI	317	346	293	0.063	-0.073	0.887	0.197
		CONT	838	860	819	0.596	-0.050	0.930	0.223
	25	SEMI	313	342	289	0.046	-0.075	0.889	0.194
		CONT	825	847	807	0.675	-0.047	0.926	0.233
60	0	SEMI	497	533	479	0.016	-0.096	0.904	0.234
		CONT	1323	1350	1309	0.281	-0.031	0.936	0.255
	10	SEMI	487	523	470	0.002	-0.086	0.904	0.224
		CONT	1290	1317	1276	0.418	-0.030	0.933	0.284
	20	SEMI	478	513	460	-0.008	-0.089	0.907	0.219
		CONT	1258	1285	1244	0.564	-0.029	0.927	0.318
	25	SEMI	472	507	454	-0.025	-0.093	0.907	0.211
		CONT	1239	1266	1226	0.640	-0.028	0.921	0.336
80	0	SEMI	665	705	652	0.013	-0.072	0.920	0.266
		CONT	1763	1794	1753	0.279	-0.018	0.942	0.336
	10	SEMI	651	692	638	-0.005	-0.068	0.921	0.257
		CONT	1719	1750	1709	0.412	-0.015	0.936	0.375
	20	SEMI	639	679	626	-0.023	-0.073	0.917	0.246
		CONT	1677	1708	1667	0.555	-0.013	0.924	0.419
	25	SEMI	631	671	618	-0.035	-0.073	0.916	0.241
		CONT	1652	1683	1642	0.633	-0.015	0.914	0.441
100	0	SEMI	833	877	823	0.007	-0.064	0.929	0.305
		CONT	2203	2237	2196	0.272	-0.022	0.939	0.398
	10	SEMI	816	861	807	-0.011	-0.066	0.925	0.291
		CONT	2148	2182	2141	0.405	-0.021	0.925	0.451

Sample Size	Percent Missing	Model	AIC	BIC	aBIC	Parameter Bias	SE bias	Coverage	Power
150	20	SEMI	801	845	791	-0.029	-0.065	0.925	0.278
		CONT	2096	2129	2088	0.547	-0.019	0.908	0.498
	25	SEMI	791	835	781	-0.043	-0.063	0.924	0.267
		CONT	2064	2098	2057	0.623	-0.021	0.898	0.524
	0	SEMI	1253	1304	1250	0.007	-0.040	0.937	0.413
		CONT	3302	3341	3300	0.270	0.001	0.936	0.565
	10	SEMI	1228	1279	1225	-0.013	-0.041	0.936	0.393
		CONT	3219	3259	3217	0.402	0.002	0.918	0.627
	20	SEMI	1205	1256	1202	-0.031	-0.041	0.934	0.373
		CONT	3141	3180	3139	0.544	0.002	0.886	0.684
200	25	SEMI	1190	1241	1187	-0.046	-0.044	0.934	0.363
		CONT	3094	3133	3092	0.619	0.000	0.866	0.709
	0	SEMI	1673	1729	1676	0.009	-0.026	0.943	0.520
		CONT	4401	4444	4403	0.265	-0.004	0.926	0.696
	10	SEMI	1640	1696	1642	-0.011	-0.028	0.940	0.493
		CONT	4291	4334	4293	0.396	-0.006	0.897	0.754
	20	SEMI	1609	1665	1611	-0.031	-0.030	0.939	0.467
		CONT	4186	4229	4188	0.537	-0.006	0.853	0.808
	25	SEMI	1589	1645	1591	-0.046	-0.033	0.938	0.449
		CONT	4124	4167	4126	0.613	-0.007	0.829	0.830
500	0	SEMI	4199	4271	4217	0.003	-0.024	0.945	0.878
		CONT	10993	11048	11006	0.257	0.007	0.890	0.976
	10	SEMI	4116	4188	4134	-0.019	-0.026	0.944	0.855
		CONT	10717	10772	10731	0.386	0.006	0.810	0.988
	20	SEMI	4038	4110	4056	-0.038	-0.022	0.944	0.836
		CONT	10455	10510	10469	0.526	0.008	0.687	0.994
	25	SEMI	3988	4060	4006	-0.053	-0.023	0.940	0.817
		CONT	10299	10354	10313	0.601	0.008	0.617	0.997