PROPERTIES OF THE SCHOOLS AND STAFFING SURVEY'S BOOTSTRAP VARIANCE ESTIMATOR

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Introduction

The National Center for Education Statistics' (NCES) Schools and Staffing Survey (SASS) conducted by the Census Bureau has a complex sample design. Public schools are selected using a stratified systematic PPS (unequal selection probabilities) sample design. From this design, data are collected at the school and school district level. The school district is an aggregation unit (i.e., the district selection probability is computed by aggregating school selection probabilities containing the district across the school strata). The probability is nonlinear with respect to the school sample sizes. A bootstrap variance estimator (Kaufman,93; sort method 4) has been developed that provides better variance estimates than the balanced half-sample replication (BHR) variance estimator for the public SASS estimates. The bootstrap variance estimator reflects the finite population correction associated with the SASS high sampling rates, without using the joint inclusion probabilities. **A set of bootstrap replicate weights are generated that work like BHR replicate weights, so that the bootstrap variances can be generated from any BHR variance software package.**

The goal of this paper is to provide results from simulation studies, concerning the SASS bootstrap variance estimator ('93 bootstrap variance estimator) described above. The '93 bootstrap variances estimator works well for the public SASS sample design, which uses square root teachers/school as the measure of size. With minor changes in the sample design (using school teacher counts as the measure of size), the school variance estimator can greatly underestimate the variance. However, with some changes, a new bootstrap variance estimator ('94 bootstrap variance estimator) performs better than BHR using the public SASS sample design, when the measure of size is either teacher or square root teacher counts. The '94 bootstrap procedure also performs better than BHR using the private SASS sample design.

First, the public and private sample designs are described, as well as the '94 bootstrap variance estimator. Then, simulation results are presented showing that the '93 bootstrap methodology can underestimate the variance under different PPS sample designs. Simulations also demonstrate that the '94 bootstrap estimator does perform better than BHR with a number of PPS sample designs.

Differences between the Bootstrap Methodologies

The '93 methodology computes school and district bootstraps together. To do this, the bootstrap frame represented both schools and districts. In order to compute the bootstrap weights, all bootstrap-schools within a bootstrap-district must be kept together (see Kaufman,93; weighting section). This restricts the sorting of the bootstrap-schools before the bootstrap sample is selected. It is this restriction that causes the '93 bootstrap estimator to underestimate the school based variance estimates, when a different measure of size is used (see table 1). However, the district variance estimates work well with the '93 methodology for each of the designs in this simulation study, and will not be discussed.

To improve the bootstrap school based variance estimates, the '94 methodology was developed, which ignores the district component of the design. Now, bootstrap-schools can be sorted without regard to the bootstrap-district associated with them. To compute district variance, the '93 methodology is still used.

Public School Sample Design

The public school survey uses NCES's public school Common Core of Data file as the frame. The frame is stratified by State, and within State by school level (elementary, secondary and combined). The school sample is selected using a systematic probability proportionate to size sampling procedure. The measure of size is the square root of the number of teachers in the school. Before sample selection, the school frame is sorted by a specific nonrandom order.

Private School Sample Design

The private school survey uses NCES's Private School Survey (PSS) file as the frame. PSS uses a list and area frame design to represent all private schools. The reason for investigating a bootstrap estimator is to find a variance estimator that reflects the finite population correction due to the large sampling rates. Since the sampling rates in the area frame are low, they will be excluded from this study. Standard methodologies can compute the area frame variances. The list frame is stratified by School Association (19 detailed groups), within Association by Census Region (4 levels), and within Region by school level (elementary, secondary and combined). The school sample is selected using a systematic probability proportionate to size sampling procedure. The measure of size is the square root of the number of teachers in the school. Before sample selection, the school frame is sorted by a specific nonrandom order.

Weighting

The school weight for school i (W_i) is $W_i = 1/p_i$ where p_i is the selection probability for school i.

Balanced Half-sample Replicates

The r[th] school half-sample replicate is formed using the usual textbook methodology (Wolter, 1985) for establishment surveys with more than 2 units per stratum. Since the SASS half-sample variances are based on 48 replicates, the simulations will be based on 48 half-sample replicates.

Three BHR variance estimates will be presented based on the methodology described above. The first (**BHR no FPC**) is the variance estimates described above. This estimate does not make any type of Finite Population Correction (FPC) adjustments.

The other two make simple FPC adjustments. The second BHR variance estimate (**BHR Prob FPC**) adjusts the first variance estimator by $1\text{-}P_h$, where P_h is the average of the selection probabilities for the selected units within stratum h.

The third BHR variance estimate (**BHR SRS FPC**) adjusts the first variance estimator by $1\text{-}n_h/N_h$, where n_h is the number of sample units in stratum h and N_h is the number of units on the frame in stratum h.

Public and Private School-Bootstrap Frame

The idea behind the bootstrap samples is to use the sample weights from the selected units to estimate the distribution of the school frame. From the estimated bootstrap-school frame, B bootstrap samples can be selected. The bootstrap-school frame is generated in the following manner:

For each selected school i, W_i bootstrap-schools (bi) are generated. If W_i has a noninteger component then a full school is generated with a reduced selection probability and weight. As shown in the bootstrap weighting section, the bootstrap expectation of the bootstrap weights (W_{bi}) equals the full-sample weight (W_i). The bi[th] bootstrap-school has the following measure of size (m_{bi}):

$$m_{bi} = I_{bi} * 1/W_i,$$

$$I_{bi} = \begin{cases} 1 & \text{if bi is an integer component of } W_i \\ C_i & \text{if bi is a noninteger component of } W_i, \\ & C_i \text{ being the noninteger component} \end{cases}$$

Bootstrap Sample Size

The bootstrap sample size is usually chosen to provide unbiased variance estimates. When the original sample is a simple random sample of size n then Efron (1982) shows a bootstrap sample size should be n-1. Sitter (1990) has computed the bootstrap sample size for the Rao-Hartley-Cochran method for PPS sampling. A variation of this result is used in this simulation. Sitter's bootstrap sample size (n^*) is the sample size which makes the following quantity closest to 1:

$$\left(\sum_{g=1}^{n^*} (N_g^{*2}-N^*)\right)/\left(\sum_{g=1}^{n}(N_g^2-N)\right)*\left(N^2-\sum_{g=1}^{n} N_g^2\right)/\left(N^* * (N^*-1)\right)$$

n^*: is the bootstrap stratum sample size
g: represents a sampling interval in the stratum
N_g^*: is the number of bootstrap-schools in the g[th] sampling interval, where the bootstrap-schools are in a random order
n: is the sample size in the stratum
N^*: is the number of bootstrap-schools in the stratum
N : is the number of schools in the stratum
N_g: is the number of schools in the g[th] sampling interval, where the schools are in their original order; either a random order for the Rao-Hartley -Cochran method or the specific nonrandom order for the SASS method

n^* can not be calculated directly. The quantity above is computed for each n^* from n-20 to n. The n^* that is closest to one is used in the bootstrap selection.

The variation to Sitter's formulation is in the computation of N_g^* and N_g. Two modifications are made. The first occurs when I_{bi} is not equal to 1. Instead, of using 1, as Sitter does when counting units; I_{bi} is used to calculate N_g^*. The second modification is due to the fact that a school or bootstrap-school can be in two sampling intervals. When this happens, N_g and N_g^* are not increased by one. Instead, they are increased by the proportion of the unit that actually goes into the sampling interval. If I_{bi} does not equal to 1, and the bootstrap-school is in two sampling intervals then N_g^* is increased by the product of the two modifications described above.

Determining the Sort Order for the '94 Bootstrap Methodology

If the bootstrap variance estimate is to work correctly, it is important that the school-bootstrap frame be randomized in an appropriate manner. In one extreme, when the bootstrap frame is sorted by the order of selection from the original sample and n^*=n, the variance estimate will be zero. In the other extreme, when the bootstrap frame is sorted randomly, the variance estimate ignores the original ordering and may overestimate the variance. Bootstrap variances will be computed using a number of sort orderings for each of the simulation samples. Coverage rates are computed for each ordering. The coverage rates are compared with estimates of the true coverage rate. The ordering associated with the coverage rates closest to the true coverage rates is the ordering that is used for the bootstrap estimator. These comparisons are made at the State level for public estimates and School Association level for private estimates. The bootstrap sort orders are described below.

School Sort Method j

Selected schools within a stratum are sorted by order of selection. Next, schools are consecutively paired within each stratum. Each pair is assigned a random number. The bootstrap-schools generated within each pair of schools are assigned bootstrap-school random numbers. If $n-n^* \le j$, for a stratum, the bootstrap-schools are sorted by bootstrap-school random number. If $n-n^* > j$, for a stratum, the bootstrap-schools are first sorted by the school pair random number; within each school pair the bootstrap-schools are sorted by the bootstrap-school random number. In other words, if the difference between the original and bootstrap sample sizes is small, as defined by j, then ignore the original sort ordering when randomizing the bootstrap-schools. Otherwise, randomize within pairs that reflect the original sort ordering.

For the public school design with square root teachers as the measure of size, two primary sorts are used (j=1 and 2). If these sorts produced underestimates or overestimates then sort method j=3 or sort method j=-1 were used, respectively. The sort ordering that provides the best coverage rates is used in the final variances. The sort order determination for the other designs in this study were done in a similar fashion.

Rationale for School Sort Method j

Sitter shows that if the number of schools in a sampling interval is constant across the intervals, then n^* will be close to n-1. If schools are sorted randomly, then the expected number of schools in the intervals is constant and n^* should be close to n-1. Therefore, if $n^*=n-1$, the assumption is that the sort ordering is effectively random, so that the school pairing should be ignored. Sort method j=1, sorts bootstrap schools randomly if $n^*=n-1$. The smaller n^* is relative to n-1, the more effective the ordering is (i.e., the ordering acts less like a random ordering) and the more important the school pairings are to the sort method. Again, this is the affect of sort method j, when j is small.

When the pairings are ignored, a bootstrap-school generated for a particular school is in more sampling intervals and therefore can be selected more often. All other things kept equal, this should increase the bootstrap variance estimate. One then expects the variance from sort method j to be ≥ the variance from sort method k, when $j \ge k$. This rule can be used to determine which sort to use to improve the variance estimate. The rule, however, does not always work. This might be due to random error or to the implicit bootstrap-school joint inclusion probabilities that are generated. The coverage rate from a particular sort that matches the true coverage rate is implicitly: 1) matching the effective randomness of the original sort (sort method j=1), adding variability as necessary (sort method j > 1), as well as, 3) matching the bootstrap-school joint inclusion probabilities to the true school joint inclusion probabilities.

Bootstrap Sample Selection

Given the bootstrap frame, m_{bi} as the measures of size, stratum bootstrap sample sizes and bootstrap-school ordering, select the bootstrap sample using the same sampling scheme as in the original sample. The bootstrap frame is randomized with each sample selection. Bootstrap-schools, generated from noncertainty schools, with measures of size larger than the sampling interval are not removed from the sampling process. If a bootstrap-school is selected more than once, the bootstrap-school weight is multiplied by the number of times it is selected.

Number of Replicates and Bootstraps

Since the SASS BHR variances are based on 48 replicates, 48 bootstrap samples are computed for each simulation sample. Given the time it take to select a set of bootstrap samples, only 60 simulation samples are used.

Bootstrap Weights

The bootstrap-school weight, W_{bi}, is:

$$W_{bi} = I_{bi} * M_{bi}/p_{bi}$$

M_{bi}: is the number of times the bi^{th} bootstrap-school is selected

p_{bi}: is the bootstrap selection probability for the bi^{th} bootstrap-school

$$E_*(\sum_{bi} W_{bi}) = \sum_{bi} I_{bi} = \sum_{i} W_i, \text{ as desired.}$$

E_*: is expectation over the bootstrap samples

Since the available data are defined by the schools selected in the original sample, a bootstrap-school weight indexed by i (BW_i) is required:

$$BW_i = \sum_{bi \in S_{iB}} W_{bi}$$

S_{iB}: is the set of all $bi \in i$ selected in the B^{th} bootstrap sample.

Sample Estimate

For each of the simulation samples, totals, averages and ratios are computed within a number of the States for the public designs, and Private school associations for the private design. The variables used are all on the sample frame. Two averages are computed using teachers and students; one ratio is computed using students and teachers; three totals are computed using students, teachers and schools. For each of the 60 simulation samples, the sample estimates and respective sample variances are computed. An estimate of the true variance for the sample estimates can be obtained by computing the simple variance of the sample estimates across the 60 simulations. The bootstrap and BHR sample variance can now be compared with the estimate of the true variance.

A number of other analysis statistics are used. They are described below.

Analysis Statistics

Coverage Rates

To measure the accuracy of the variance estimates, a one sigma two-tailed coverage rate is computed by determining what proportion of the time the population estimate is within the respective confidence interval. If the estimates are approximately normal then the coverage rates should be close to 0.68.

Coverage Rate Bias (**Bias**)

$$\text{Bias} = R_e - R_t$$

R_e: is the coverage rate based or either a bootstrap or BHR variance estimate

R_t: is an estimate of the true coverage rate. For a given estimator, it is based on the simple variance of the simulation estimates for that estimator

Results based on Bias in the Coverage Rates

Table 1 shows how the '93 bootstrap methodology underestimates the school based variance when teachers/school is used as the measure size. 28 percent of the time, the variance for averages (**AVE**) has a very large negative bias (**BIAS** LT -.14). The variance for totals (**TOTAL**) has a very large negative bias 32 percent of the time. These are unacceptable rates. If a general methodology exits, the '93 methodology isn't a general method.

The '94 bootstrap variance estimator (**94 BOOT**) works much better than the '93 bootstrap estimator for a number of sample designs (public SASS design, private SASS design and public SASS design using teachers/school as the measure of size). It also works better than BHR, even when simple finite populations correction adjustments (FPC) are applied to the BHR variance estimates. The results are discussed below for each design.

SASS Public School Design (Tables 2-4)

For school averages, 52 percent of the '94 bootstrap variance estimates have a small bias (**BIAS** between -.07 to .07). BHR without any FPC adjustments (**BHR No FPC**) only has 20 percent of the variance estimates in this category. If simple FPC adjustments are applied to **BHR No FPC** the percentage increases to 48 and 44 percent for **BHR Prop FPC** and **BHR SRS FPC**, respectively. The bootstrap estimator has only one state (4 percent) which has a very large overestimate (**BIAS GE .14**), while **BHR No FPC** has 44 percent in this category. Applying simple FPC adjustment helps, but there are still a reasonable number of states with large overestimates. For the bootstrap estimator, no states have very large underestimates (**BIAS LT -.14**), while each BHR estimator has 8 percent in the very large underestimate category.

The results for school totals are similar to school averages discussed above. 56 percent of the '94 bootstrap variances are in the small bias category, while **BHR No FPC** has only 32 percent in this category. Applying an FPC helps, but the '94 bootstrap method is better. The bootstrap estimator has 12 percent of the estimates in the very large bias category, while **BHR No FPC** has 40 percent in this category. An FPC adjustment reduces the cases to 24 percent. The bootstrap estimator has no states with very large underestimate. **BHR No FPC** likewise has no cases in this category, but the FPC adjusted variances each have 8 percent of the states in this category.

For ratio estimates, the 94 bootstrap and FPC adjusted BHR variances work well. The only problem with the **BHR No FPC** variances is that 24 percent of the states are in the very large overestimate category.

SASS Private School Design (Tables 5-7)

For school averages, 63 percent of the '94 bootstrap variance estimates have a small bias (**BIAS** between -.07 to .07). BHR without any FPC adjustments

(**BHR No FPC**) only has 47 percent of the variance estimates in this category. If simple FPC adjustments are applied to **BHR No FPC** the percentage increases to 53 percent for both **BHR Prop FPC** and **BHR SRS FPC**. 11 percent of the bootstrap estimates are very large overestimates (**BIAS GE .14**), while **BHR No FPC** has 26 percent in this category. Applying simple FPC adjustment helps, but the bootstrap method is still better. For the bootstrap estimator, one association (5 percent) has a very large underestimate (**BIAS LT -.14**), while none of the BHR estimators have any associations in this category.

The results for school totals are similar to school averages discussed above. 74 percent of the 94 bootstrap variances are in the small bias category, while **BHR No FPC** has only 32 percent in this category. Applying an FPC helps, but the bootstrap method is still better. The bootstrap estimator has 11 percent of the estimates in the very large bias category, while **BHR No FPC** has 26 percent in this category and the FPC adjusted BHR methods are in between. Neither the bootstrap nor BHR estimators have any variances in the very large underestimate category.

For ratio estimates, the 94 bootstrap and FPC adjusted BHR variances work well. The only problem with the **BHR No FPC** variances is that 21 percent of the variances are in the very large overestimate category.

SASS Public School Design - Measure of Size, Teachers (Tables 8-10)

Overall, the 94 Bootstrap variances are better than the BHR variances. However, the differences are not as great with this design. For averages, 76 percent of the bootstrap variances are in the small bias category, while the other methods' percentage are in the sixties. None of the methodologies have very large overestimates, while only the FPC adjusted BHR estimates have a few very large underestimates (8 and 12 percent).

For totals, 76 percent of the 94 bootstrap variances are in the small bias category. **BHR no FPC**, **BHR prob FPC** and **BHR SRS FPC** have 64, 80 and 76 percent in this category, respectively. None of the methodologies have very large overestimates, while all the methodologies have a few very large underestimates (4 to 8 percent).

For ratios, all the methodologies, except **BHR no FPC**, work equally well. They all have between 52 and 56 percent in the small bias category; except **BHR no FPC**, which has only 44 percent in the small bias category. All methods have some, but minimal cases in the very large underestimate category (4 to 8 percent); and they all have substantial cases in the very large overestimate category (16 to 28 percent).

Results based on Coverage Rates of National Estimate (Table 11)

Instead of analyzing the coverage rate bias distributions by state or association, another perspective is analyzing coverage rate biases for national estimates. Since the simulations are done by a series of different sets of states, the only national estimate that can be computed are totals. The national coverage rate biases are provided in table 11. The table shows that the bootstrap biases are all less than 1 percent. The **BHR no FPC** biases vary, but are all much larger then the bootstrap bias. They range for 8.3 to 11.7 percent, depending on the type of design . The FPC adjusted BHR biases are slightly smaller than the **BHR no FPC** biases. They range from 3.3 to 7.3 percent, depending on the design.

Other Results

Another way of evaluating the bootstrap methodology is to compute the mean square error (MSE), instead of the coverage rates. These results are similar to those presented here. The MSE results are provided in an upcoming NCES working paper.

References

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Table 1 - State Distribution of the Coverage Rate Bias in 93 Bootstrap Standard Errors using Number of Teachers as the Measure of Size

Bias Col Pct	AVE	RATIO	TOTAL
LT -.14	28.00	8.00	32.00
[-.14, -.07)	28.00	16.00	28.00
[-.07, 0.0)	24.00	40.00	28.00
[0.0, .07)	8.00	16.00	4.00
[.07, .14)	8.00	12.00	8.00
GE .14	4.00	8.00	0.00

Table 2 - State Distribution of the Coverage Rate Bias in the 94 Bootstrap Estimator for the SASS Public Design Estimating School Averages

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -.14	0.00	8.00	8.00	8.00
[-.14, -.07)	4.00	0.00	0.00	0.00
[-.07, 0.0)	20.00	16.00	16.00	4.00
[0.0, .07)	32.00	32.00	28.00	16.00
[.07, .14)	40.00	32.00	28.00	28.00
GE .14	4.00	12.00	20.00	44.00

Table 3 - State Distribution of the Coverage Rate Bias in the 94 Bootstrap Estimator for the SASS Public Design Estimating School Totals

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -.14	0.00	8.00	8.00	0.00
[-.14, -.07)	4.00	0.00	0.00	4.00
[-.07, 0.0)	20.00	12.00	8.00	8.00
[0.0, .07)	36.00	24.00	28.00	24.00
[.07, .14)	28.00	32.00	32.00	24.00
GE .14	12.00	24.00	24.00	40.00

Table 4 - State Distribution of the Coverage Rate Bias in the 94 Bootstrap Estimator for the SASS Public Design Estimating School Ratios

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -.14	4.00	0.00	0.00	0.00
[-.14, -.07)	28.00	16.00	16.00	4.00
[-.07, 0.0)	16.00	32.00	32.00	12.00
[0.0, .07)	44.00	20.00	20.00	40.00
[.07, .14)	4.00	24.00	24.00	20.00
GE .14	4.00	8.00	8.00	24.00

Table 5 - Assoc. Distribution of the Coverage Rate Bias in 94 Bootstrap Estimator for the SASS Private Design Estimating School Averages

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -0.14	5.26	0.00	0.00	0.00
[-.14, -.07)	15.79	15.79	15.79	0.00
[-0.07, 0.0)	15.79	10.53	5.26	5.26
[0.0, .07)	47.37	42.11	47.37	42.11
[.07, .14)	5.26	15.79	15.79	26.32
GE .14	10.53	15.79	15.79	26.32

Table 6 - Assoc. Distribution of the Coverage Rate Bias in 94 Bootstrap Estimator for the SASS Private Design Estimating School Totals

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
[-.14, -.07)	10.53	0.00	0.00	0.00
[-0.07, 0.0)	26.32	10.53	5.26	0.00
[0.0, .07)	47.37	52.63	52.63	31.58
[.07, .14)	5.26	21.05	21.05	42.11
GE .14	10.53	15.79	21.05	26.32

Table 7 - Assoc. Distribution of the Coverage Rate Bias in 94 Bootstrap Estimator for the SASS Private Design Estimating School Ratios

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -0.14	10.53	10.53	5.26	5.26
[-.14, -.07)	5.26	5.26	10.53	5.26
[-0.07, 0.0)	26.32	15.79	15.79	10.53
[0.0, .07)	42.11	42.11	36.84	42.11
[.07, .14)	5.26	10.53	15.79	15.79
GE .14	10.53	15.79	15.79	21.05

Table 8 - State Distribution of the Coverage Rate Bias in 94 Bootstrap Estimator for the SASS Public Design using Teachers/School as the Measure of Size Estimating School Averages

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -.14	0.00	12.00	8.00	0.00
[-.14, -.07)	20.00	24.00	16.00	12.00
[-.07, 0.0)	48.00	44.00	44.00	28.00
[0.0, .07)	28.00	20.00	24.00	40.00
[.07, .14)	4.00	0.00	8.00	20.00

Table 9 - State Distribution of the Coverage Rate Bias in 94 Bootstrap Estimator for the SASS Public Design using Teachers/School as the Measure of Size Estimating School Totals

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -.14	4.00	8.00	4.00	4.00
[-.14, -.07)	16.00	8.00	8.00	0.00
[-.07, 0.0)	44.00	56.00	36.00	20.00
[0.0, .07)	32.00	24.00	40.00	44.00
[.07, .14)	4.00	4.00	12.00	32.00

Table 10 - State Distribution of the Coverage Rate Bias in 94 Bootstrap Estimator for the SASS Public Design using Teachers/School as the Measure of Size Estimating School Ratios

Bias Col Pct	94 BOOT	BHR Estimators Prob FPC	SRS FPC	No FPC
LT -.14	4.00	8.00	4.00	4.00
[-.14, -.07)	4.00	8.00	4.00	0.00
[-.07, 0.0)	28.00	16.00	24.00	0.00
[0.0, .07)	28.00	36.00	28.00	44.00
[.07, .14)	16.00	16.00	20.00	24.00
GE .14	20.00	16.00	20.00	28.00

Table 11 -- Coverage Rate Bias (Percent) for National Estimates of Totals by Sample Design and Variance Estimator

Type of Design Measure of Size	94 BOOT	BHR Prob FPC	SRS FPC	No FPC
Public School SASS Square Root Teachers	0.6	3.3	3.9	5.6
Public School SASS Teachers	-0.7	5.0	5.6	8.3
Private School SASS Square Root Teachers	0.6	7.3	7.3	11.7