

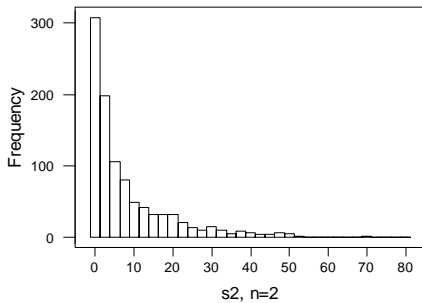
## STA362: Introduction to Statistics

### Illustration of the sampling distribution of $s^2$

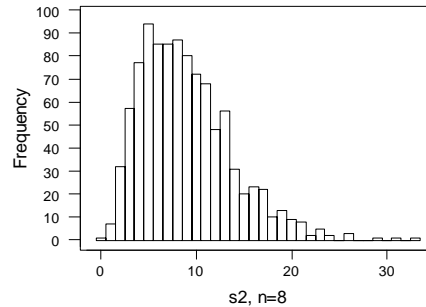
Since we often will be using sample data to infer about a population mean  $\mu$ , we might also have to use the sample standard deviation  $s$  as an estimator of the population standard deviation  $\sigma$ . Thus, it is useful to know about the sampling distribution for this measure of variability. Unfortunately,  $s$  is a statistic that doesn't behave like  $\bar{x}$  from sample to sample. Distributional theory dictates that we study the sampling distribution of  $s^2$  (not  $s$ ), and that we **assume the population from which sampling takes place is normal to begin with** (not a CLT assumption).

Here are four 1000-rep simulated sampling distributions of  $s^2$  from a normal population with  $\mu = 10$  and  $\sigma = 3$  (i.e.,  $\sigma^2 = 9$ ). We observe the behavior of  $s^2$  under a variety of sample sizes:  $n = 2$ ,  $n = 8$ ,  $n = 20$ , and  $n = 50$ .

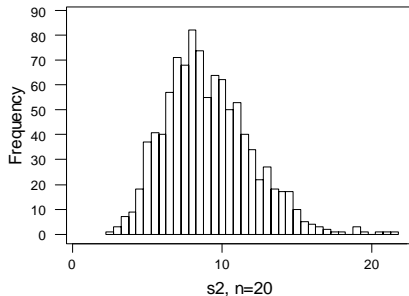
Sampling distribution of sample variance



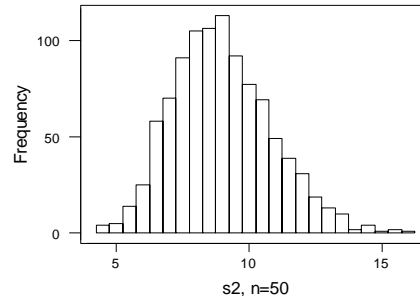
Sampling distribution of sample variance



Sampling distribution of sample variance



Sampling distribution of sample variance



Note that the shape of this distribution always remains positively skewed, even for large  $n$ . This will always be true of the sampling distribution of the sample variance  $s^2$ . Also, the severity of the skew lessens as the sample size increases, so a good distributional model for this statistic must reflect this. In class, we will develop the **chi-square ( $\chi^2$ ) distribution** for modeling the sampling distribution of the sample variance  $s^2$ .

We note here (without simulation proof) that the resulting sampling distributions for  $s^2$  would differ dramatically from the above illustrated behavior were we sampling from a distinctly non-normal population. The normality assumption for the originating population is crucial to ensure the accuracy of the  $\chi^2$  model.