Byrne Chapter 12 – Bootstrapping

1. Central limit theorem
   1. We are using large samples -> with the central limit theorem large samples will approach normality, even if the underlying population may not be totally normal
   2. However, we all know that sometimes this does not happen
   3. Especially if you use likert scale data, which is not technically continuous.
2. Why non-normal data is bad
   1. Adversely affects chi-square (which causes you to change things you might not need to)
   2. Smaller samples will be adversely affected by chi-square
   3. CFI and TLI are decreased
   4. Very low standard errors, which make paths look significant that might not be
3. Bootstrapping – the idea
   1. You take a large sample and treat it like the “population”. Then samples of the same “type” are taken and tested on your model. The procedure repeats so you are getting an average estimate of the max likelihood data (so the highest probability of the estimation, averaged over the many fake samples you’ve taken from this population).
   2. Bootstrap is free from the normality restriction! Whoo!
   3. The great idea is to be able to test if your mean and standard error (or estimates and standard error) are stable if you were to sample the population over and over again.
   4. Good and bads:
      1. Gives you a good idea if the estimates are going to hold, especially when non-normal
      2. Does assume that your sample is representative of the population (errr…)
      3. Independence assumption must be met (all participants are separate and did not influence each other)
      4. Degree to which the samples are consistent
      5. When the data is normal, then bootstrap is a bit biased
4. Limitations
   1. Not the answer to small sample sizes
   2. Helps with standard errors, but not the end all be all
   3. Bootstrap may not work
   4. Set a path to 1 (which we’ve been doing all year)
5. To get amos to run:
   1. View > Analysis properties > bootstrap
   2. Check for kurtosis, skew, and outliers