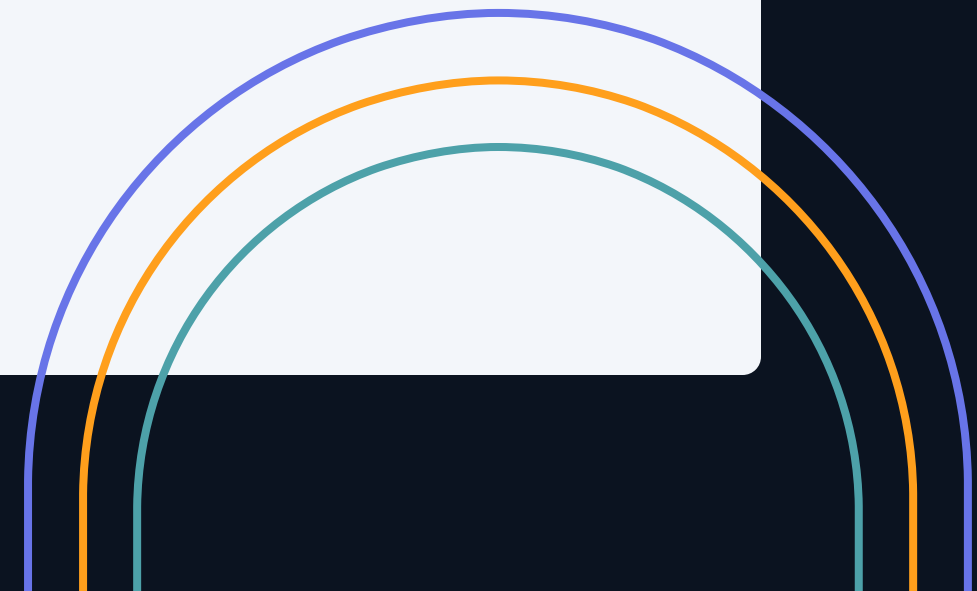




# A Comparative Simulation Study on Various Equality of Variance Tests

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# Why do we care?

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- **Variance is a measure of how far data points are from the mean**
- **Statistics is an essential component of every study**
- **Numerous statistical testing assume homogeneity of variance**
- **Experimental data is messy**
- **Goal : With several choices of equality of variance testing, we want to identify the best test to use given different types of data**

1. **Test For Equality of Group Variances**
2. **Brown Forsythe vs Levene's Test**
3. **Bootstrap Testing**
4. **Methodology**
5. **Results**
6. **Conclusion & Discussion**
7. **Future Directions**

# Outline

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# Test for Equality of Group Variances

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What does the test do?

Identify whether the variances between 2 groups are different

How does the test work?

**Null Hypothesis ( $H_0$ )** : The group variances are equal

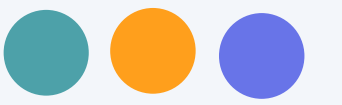
**Alternative Hypothesis ( $H_A$ )** : The group variances are not equal

Returns a **p-value**

**Significance level ( $\alpha$ ) = 0.05**

p-value < 0.05 → Reject  $H_0$

p-value > 0.05 → Do not reject  $H_0$



## Levene's Test

- Uses deviations from group means
- Gives the best power for symmetric, moderate tailed distributions

## Brown-Forsythe

- Uses deviations from group medians
- More robust to skewness and unequal sample sizes

# Bootstrap Testing



- **What is Bootstrap Testing?**

**A form of hypothesis testing that involves resampling a single data set to create a multitude of simulated samples**

- **Advantages of bootstrap Testing**

**This approach doesn't assume any underlying distribution of the data since the sampling distribution can be observed.**

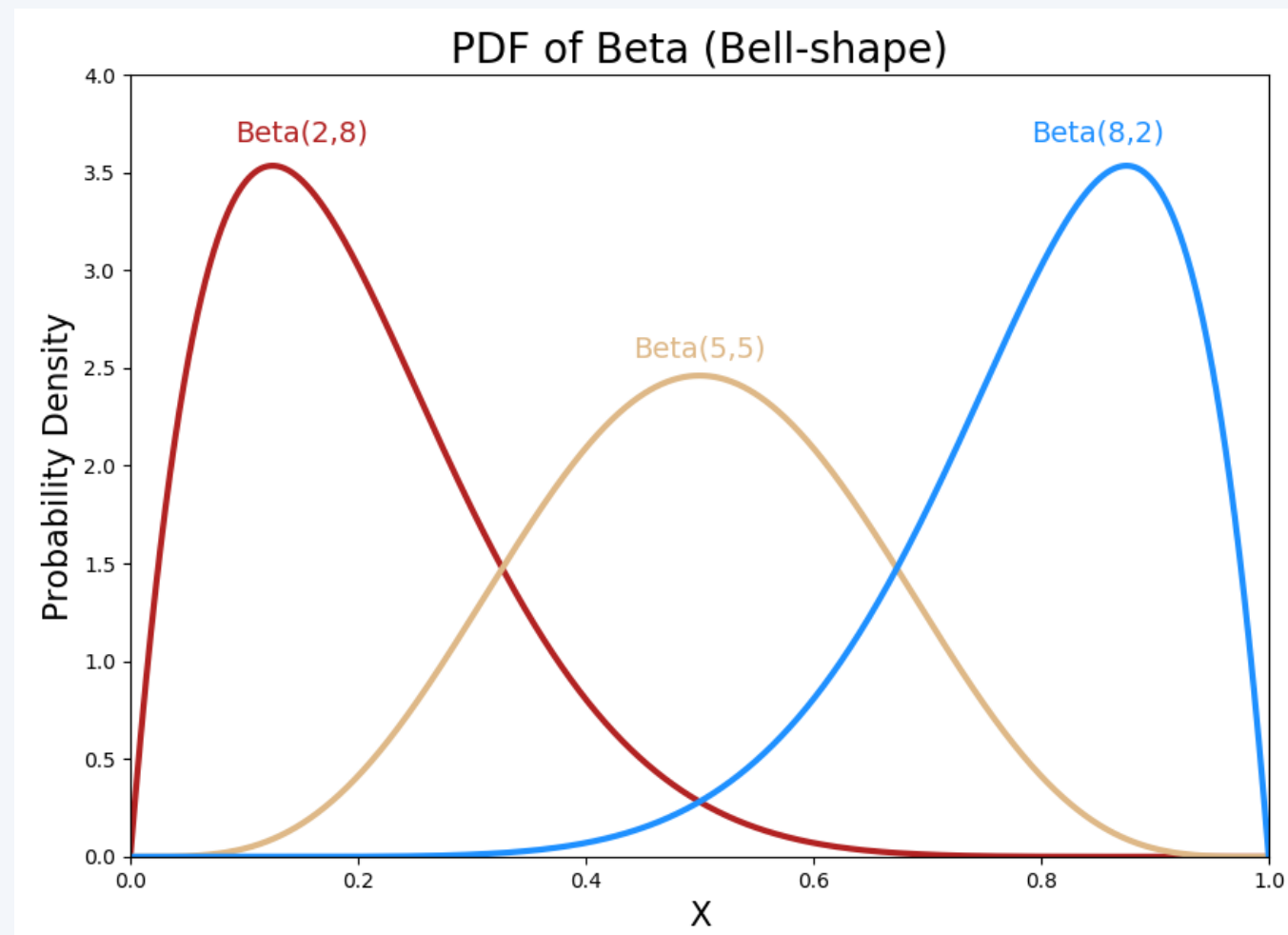
- **In our case:**

**We resample our median deviances and construct a sampling distribution from which we will infer a p-value**

# Methodology

Conduct a simulation study in R

1. Generate data from beta distribution



Source : <https://vitalflux.com/beta-distribution-explained-with-python-examples/>

Data used in this study:

- Beta distribution of skew 0 – 3
- 5 Variance ratio (1:1 to 1:5)
- Sample size of 50 and 100

We are using:

$4 \times 5 \times 2 = 40$  different settings

# Methodology

**2. Perform all 3 tests on the data**

**3. Collect p values**

**4. Repeat 10,000 times**

**5. Test for type 1 and type 2 errors**

- Type I error = falsely reject null hypothesis

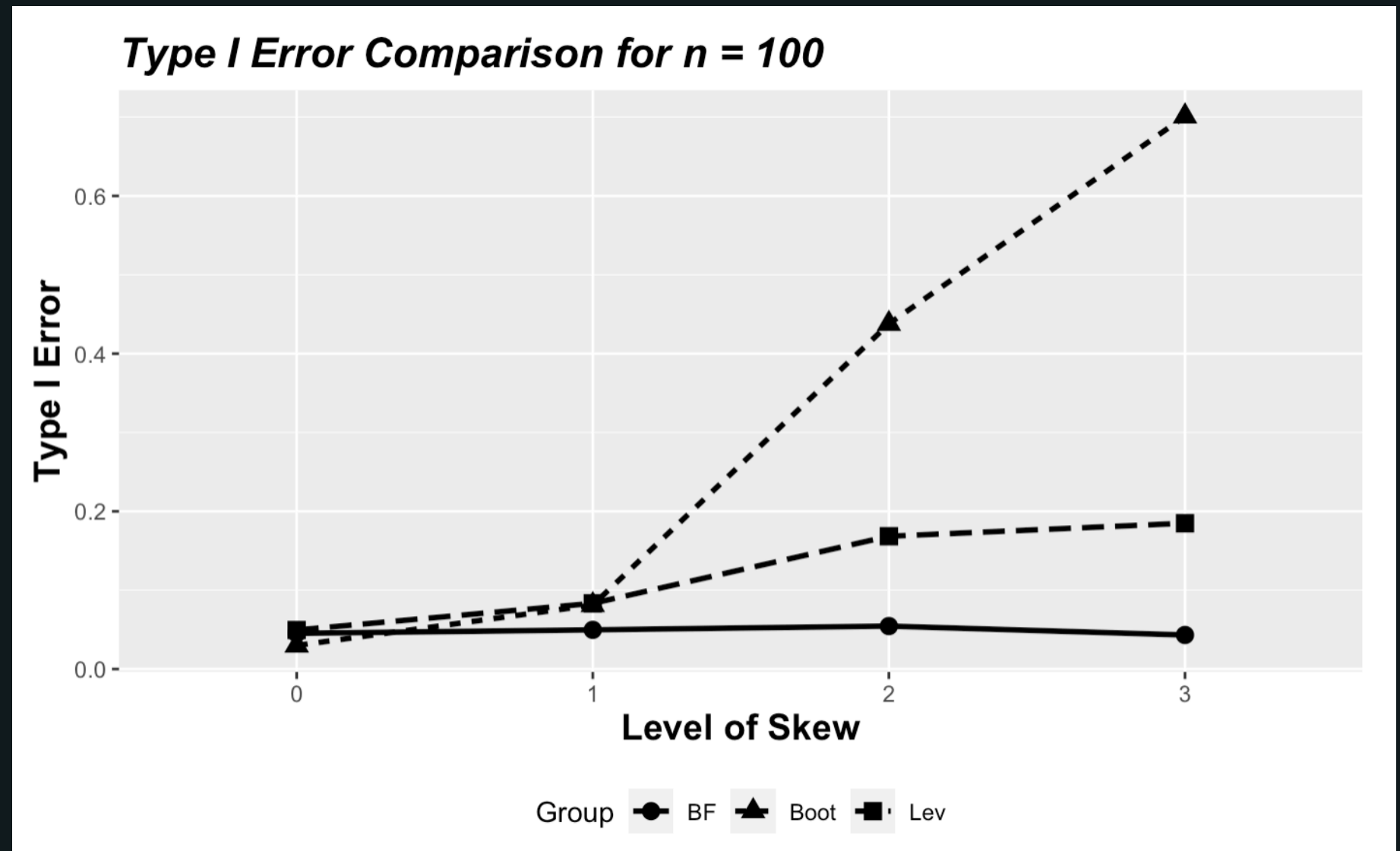
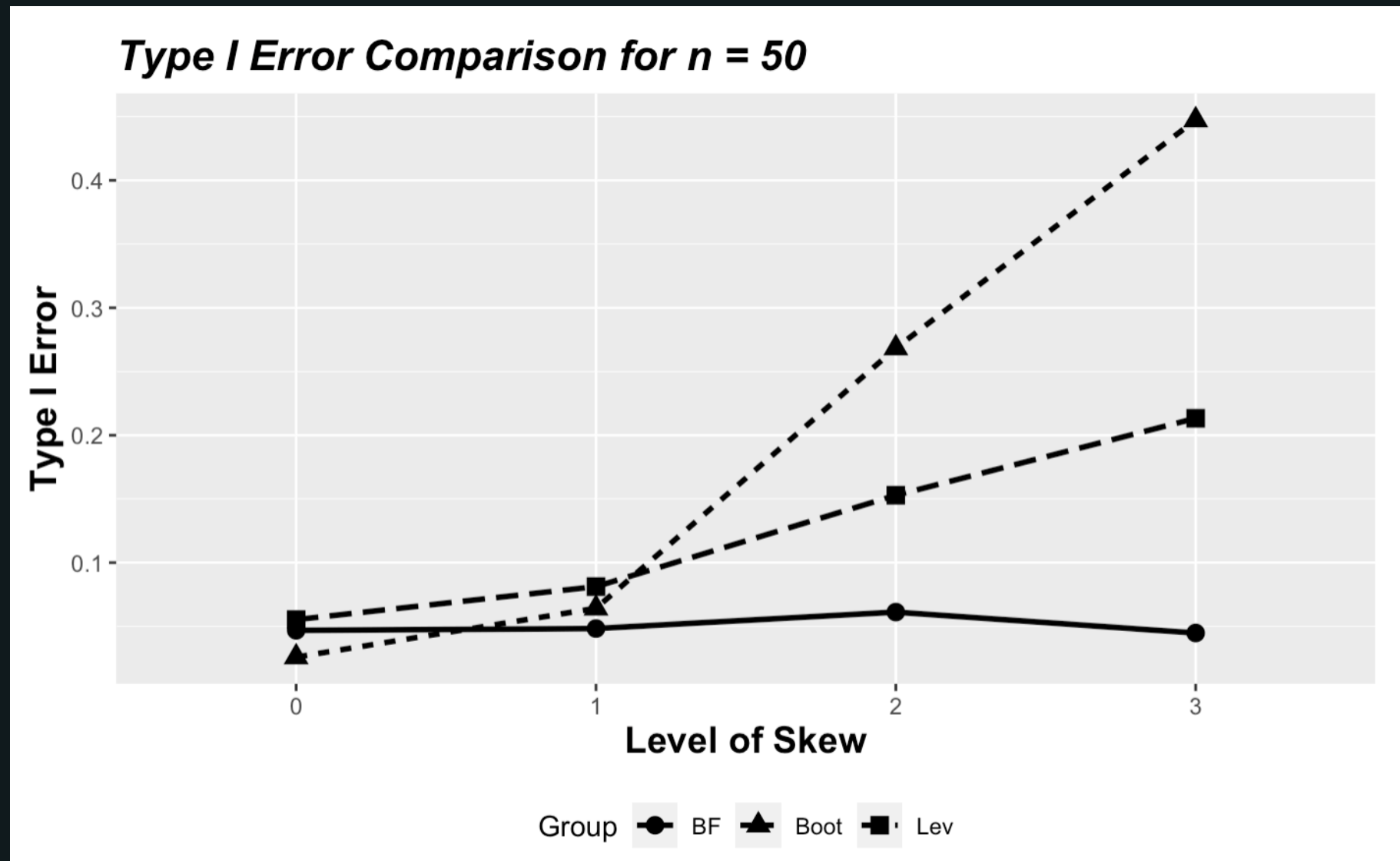
- Type II error = fail to reject null hypothesis

**We test type I error for data with Variance ratio 1:1**

**We test type II error for data with Variance ratio 1:2 – 1:5**



# Results

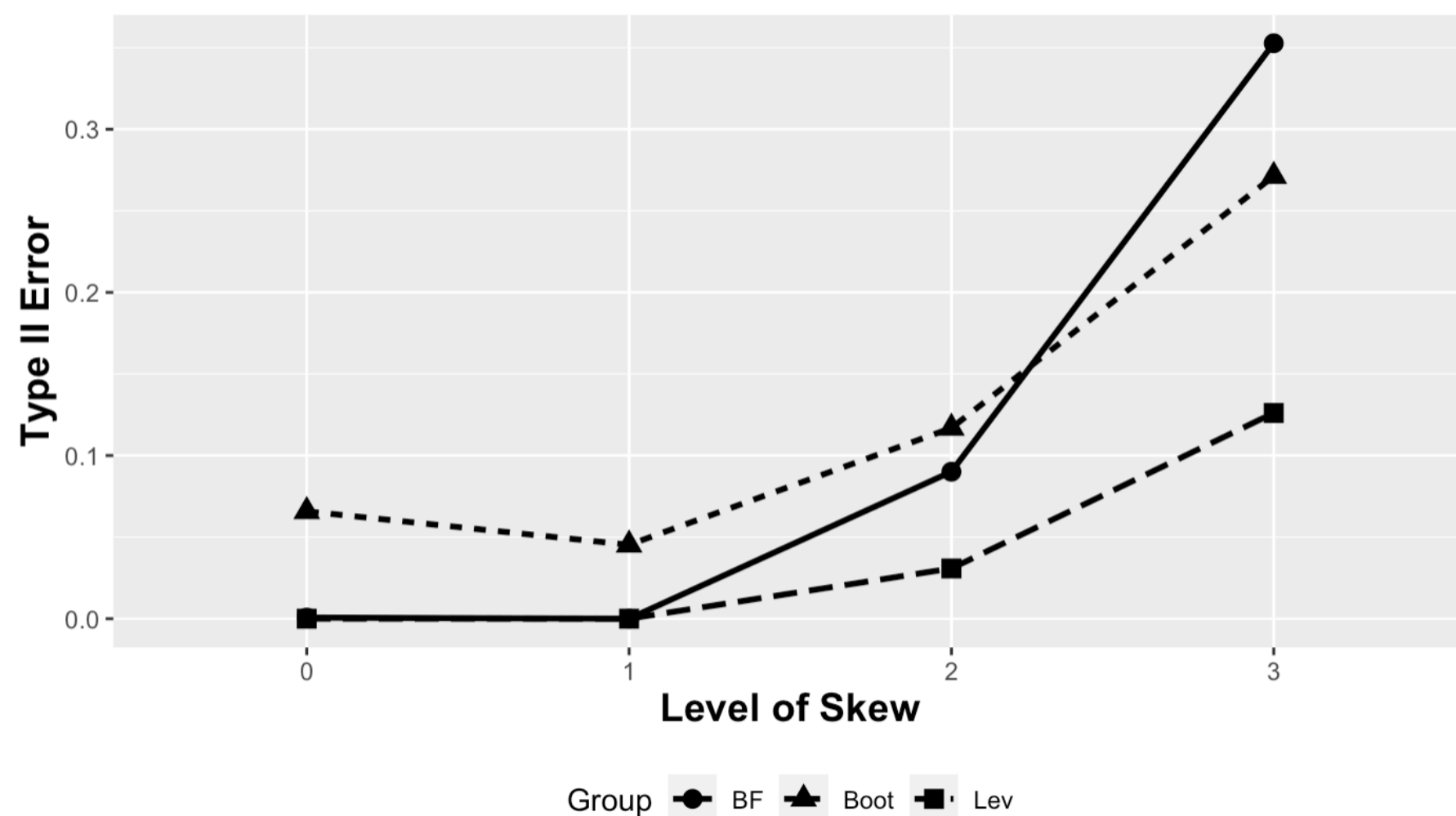


- Brown Forsythe Test returns the lowest Type I Error level, of average 0.049 for all level of skewness and both  $n = 50$  and  $n = 100$
- All the test performed similarly for skew level 0,1, but error level shoots up for both Levene's and bootstrap when skew  $\geq 2$ .

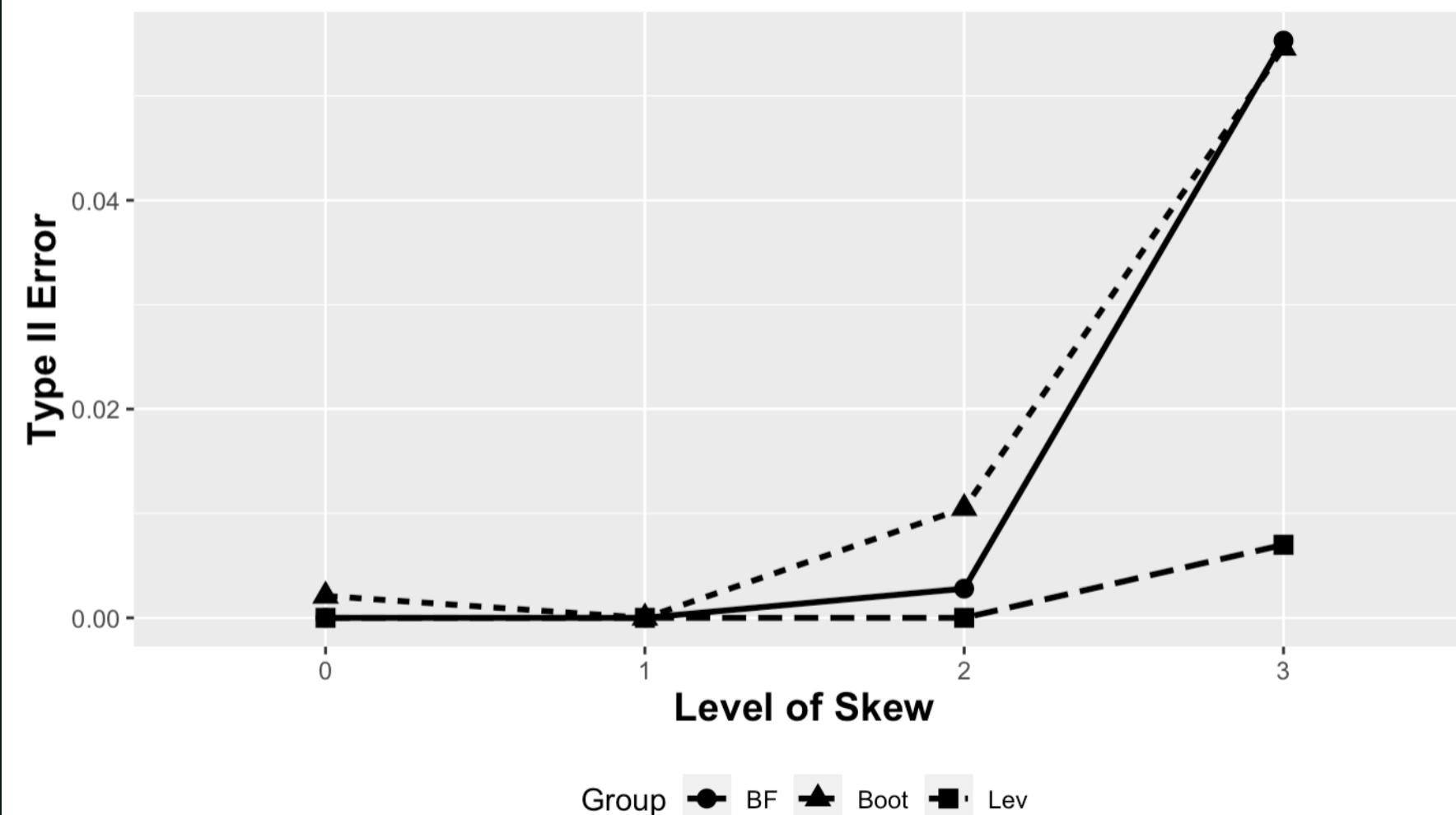
# Results



Type II Error Comparison for Variance Ratio 1:5,  $n = 50$



Type II Error Comparison for Variance Ratio 1:5,  $n = 100$



- All the test return a low level of Type II error even when the data is skewed
- Since the error level  $< 0.35$  when  $n = 50$ , and error level  $< 0.06$  when  $n = 100$ , the test are sensitive to sample size
- As the variance ratio increases, type II error decreases

# Conclusion & Discussion

- BF outperforms the other tests across all level of skews, for groups with equal sample sizes
- Unexpected type I error for bootstrap testing
- If type I error is larger, then it is expected for type 2 to be smaller

## Future Directions

- Improve bootstrap testing performance
- Evaluate the tests' performances on datasets with different sample sizes

**THANK YOU!**

