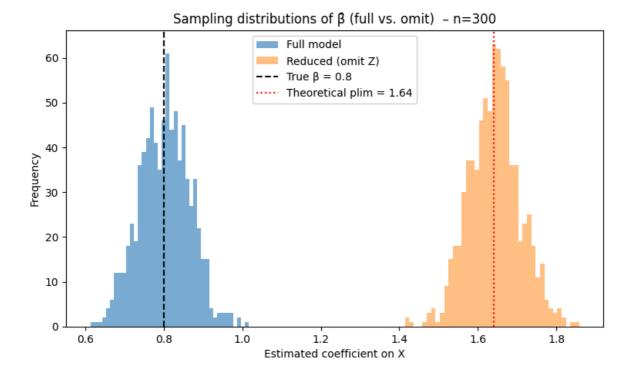
```
In [1]: import matplotlib.pyplot as plt
         import numpy as np
         import pandas as pd
         import statsmodels.api as sm
         from statsmodels.api import OLS, add_constant
         from statsmodels.tsa.statespace.sarimax import SARIMAX
         plt.rcParams["figure.figsize"] = (16, 9) # Figure size and width
In [2]: #Omitted Variable Bias Simulation
         #Data-generating process
         alpha = 0.0
                             # intercept
         beta = 0.8
                             # true coefficient on X
        delta = 1.2  # effect of omitted Z
rho = 0.7  # corr(X,Z)
sigma_eps = 0.8  # SD of epsilon
In [3]: # Monte-Carlo settings
         sample_sizes = [50, 300, 2000] # small, medium, large n
                                            # repetitions
         reps = 800
         selected_n = 300
                                            # size for histogram plot
         np.random.seed(4242)
                                           # reproducibility
In [4]: #Simulation Loop
         summary_rows = []
         beta_full_sel = None
         beta_omit_sel = None
         for n in sample_sizes:
             beta_full = np.empty(reps)
             beta omit = np.empty(reps)
             for r in range(reps):
                 # Generate correlated X and Z
                 X = np.random.normal(0, 1, n)
                 u = np.random.normal(0, 1, n)
                 Z = \text{rho} * X + \text{np.sqrt}(1 - \text{rho}**2) * u
                 # Outcome
                 eps = np.random.normal(0, sigma eps, n)
                 Y = alpha + beta * X + delta * Z + eps
                 # Full model: Y \sim X + Z
                 X \text{ full} = \text{add constant(np.column stack((X, Z)))}
                 beta_full[r] = OLS(Y, X_full).fit().params[1]
                 # Reduced model: Y ~ X (omit Z)
                 X_red = add_constant(X)
                 beta_omit[r] = OLS(Y, X_red).fit().params[1]
             if n == selected n:
                 beta_full_sel = beta_full
                 beta_omit_sel = beta_omit
```

```
summary_rows.append({
                "n": n,
                "mean_beta_full": beta_full.mean(),
                "sd_beta_full": beta_full.std(ddof=1),
                "bias_beta_full": beta_full.mean() - beta,
                 "mean_beta_omit": beta_omit.mean(),
                "sd_beta_omit": beta_omit.std(ddof=1),
                "bias_beta_omit": beta_omit.mean() - beta
            })
        summary = pd.DataFrame(summary_rows)
        print("\nMonte Carlo Summary\n", summary)
       Monte Carlo Summary
              n mean_beta_full sd_beta_full bias_beta_full mean_beta_omit \
       0
            50
                      0.798122
                                    0.166567
                                                   -0.001878
                                                                     1.637012
       1
           300
                      0.801978
                                    0.063730
                                                    0.001978
                                                                     1.642243
                      0.800746
       2 2000
                                    0.024714
                                                    0.000746
                                                                    1.641987
          sd_beta_omit bias_beta_omit
              0.172766
                            0.837012
       a
              0.065205
                              0.842243
       2
              0.025419
                             0.841987
In [5]: #Theoretical probability limit
        plim_omit = beta + delta * rho
        print(f"\nTheoretical plim of \beta_hat (omit Z) = {plim_omit:.3f}")
       Theoretical plim of \beta_{hat} (omit Z) = 1.640
In [6]: #Plots
        # Histogram of sampling distributions at n=300
        plt.figure(figsize=(9,5))
        plt.hist(beta_full_sel, bins=40, alpha=0.6, label="Full model")
        plt.hist(beta_omit_sel, bins=40, alpha=0.5, label="Reduced (omit Z)")
        plt.axvline(beta, color="black", ls="--", label=f"True \beta = {beta}")
        plt.axvline(plim_omit, color="red", ls=":", label=f"Theoretical plim = {plim_omi
        plt.title("Sampling distributions of \beta (full vs. omit) - n=300")
        plt.xlabel("Estimated coefficient on X")
        plt.ylabel("Frequency")
        plt.legend()
        plt.show()
```



```
In [7]: # Mean estimate vs. sample size

plt.figure(figsize=(8,5))
plt.plot(summary["n"], summary["mean_beta_full"], "o-", label="Mean β^full")
plt.plot(summary["n"], summary["mean_beta_omit"], "s--", label="Mean β^omit Z")
plt.axhline(beta, color="black", ls="--", label=f"True β = {beta}")
plt.axhline(plim_omit, color="red", ls=":", label=f"Theoretical plim = {plim_omit plt.xscale("log")
plt.xticks(summary["n"], summary["n"])
plt.title("Monte Carlo mean of β^vs. sample size")
plt.xlabel("Sample size (log scale)")
plt.ylabel("Mean estimated coefficient on X")
plt.legend()
plt.show()
```

## Monte Carlo mean of β vs. sample size 1.6 Mean β full Mean β omit Z True β = 0.8 Theoretical plim = 1.64 50 Sample size (log scale)

#Summary The coefficient on X for the full model is unbiased; around the true value  $\beta$ =0.8 The coefficient is larger in the reduced model; about 1.64 which is equal to the theoretical probability limit=  $\beta$ + $\delta\rho$ =0.8+1.2×0.7=1.64 The sampling variance shrinks in the full model as n grows. The sampling variance also shrinks as n increases in the reduced model and the centre stays at 1.64 In conclusion, increasing the sample size does not eliminate omitted-variable bias. It only reduces random sampling error.