

Questions

- (a) Consider again the case from the lecture, with

$$\text{DGP: } y = X_1\beta_1 + X_2\beta_2 + \varepsilon \rightarrow b_1 \text{ and } b_2$$

$$\text{Model: } y = X_1\beta_1 + \tilde{\varepsilon} \rightarrow b_R$$

Prove $\text{Var}(b_R) = \text{Var}(b_1) - P\text{Var}(b_2)P'$. Use $b_R = b_1 + Pb_2$ and $\text{Cov}(b_2, b_R) = 0$ (you do not need to prove this).

- (b) One way to get more insight into the bias-efficiency trade-off (also referred to as the bias-variance trade-off) is to combine bias and efficiency in the Mean Squared Error (MSE). The mean squared error is defined as

$$MSE(b) = E((b - \beta)(b - \beta)'),$$

with b a certain estimator of the unknown parameter β . Prove $E((b - \beta)(b - \beta)') = \text{Var}(b) + E(b - \beta)E(b - \beta)'$. Hints: First write the MSE out in four terms. Then, as an intermediate step, show $\text{Var}(b) = E(bb') - E(b)E(b)'$. Finally, add and subtract $E(b)E(b)'$ from the MSE expression and rewrite to get the desired result.

- (c) Again in the context of the case from the lecture (see (a)), show that the mean squared error of b_1 minus the mean squared error of b_R is equal to

$$MSE(b_1) - MSE(b_R) = P(\text{Var}(b_2) - \beta_2\beta_2')P'.$$

- (d) When would the restricted estimator be better, when basing this decision on the mean squared error?