because $Mi = 0$.

$$MX\hat{\beta} = \begin{pmatrix} 0 & MX_2 \end{pmatrix} \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{pmatrix} = MX_2\hat{\beta}_2.$$

Thus,

$$My = MX\hat{\beta} + Me \qquad \Longrightarrow \qquad My = MX_2\hat{\beta}_2 + e.$$

$y'My$ is given by: $y'My = \hat{\beta}_2' X_2' MX_2\hat{\beta}_2 + e'e$, because $X_2'e = 0$ and $Me = e$.

The coefficient of determinant, R^2, is rewritten as:

$$R^2 = 1 - \frac{e'e}{y'My} \qquad \Longrightarrow \qquad e'e = (1 - R^2)y'My,$$

$$R^2 = \frac{y'My - e'e}{y'My} = \frac{\hat{\beta}_2' X_2' MX_2\hat{\beta}_2}{y'My} \qquad \Longrightarrow \qquad \hat{\beta}_2' X_2' MX_2\hat{\beta}_2 = R^2 y'My.$$

Therefore,

$$\frac{\hat{\beta}_2' X_2' MX_2\hat{\beta}_2/(k-1)}{e'e/(n-k)} = \frac{R^2 y'My/(k-1)}{(1-R^2)y'My/(n-k)} = \frac{R^2/(k-1)}{(1-R^2)/(n-k)} \sim F(k-1, n-k).$$

Thus, using R^2, the null hypothesis $H_0 : \beta_2 = 0$ is easily tested.

5 Restricted OLS (制約付き最小二乗法)

1. Let $\tilde{\beta}$ be the restricted estimator.

   Consider the linear restriction: $R\beta = r$.

2. Minimize $(y - X\tilde{\beta})'(y - X\tilde{\beta})$ subject to $R\tilde{\beta} = r$.

   Let L be the Lagrangian for the minimization problem.

$$L = (y - X\tilde{\beta})'(y - X\tilde{\beta}) - 2\tilde{\lambda}'(R\tilde{\beta} - r)$$

   Let $\tilde{\beta}$ and $\tilde{\lambda}$ be the solutions of β and λ in the optimization problem shown above.

   That is, $\tilde{\beta}$ and $\tilde{\lambda}$ minimize the Lagrangian L.

Therefore, we solve the following equations:

$$\frac{\partial L}{\partial \tilde{\beta}} = -2X'(y - X\tilde{\beta}) - 2R'\tilde{\lambda} = 0$$
$$\frac{\partial L}{\partial \tilde{\lambda}} = -2(R\tilde{\beta} - r) = 0.$$

(*) Remember that $\dfrac{\partial a'x}{\partial x} = a$ and $\dfrac{\partial x'Ax}{\partial x} = (A + A')x$.

From $\dfrac{\partial L}{\partial \tilde{\beta}} = 0$, we obtain:

$$\tilde{\beta} = (X'X)^{-1}X'y + (X'X)^{-1}R'\tilde{\lambda} = \hat{\beta} + (X'X)^{-1}R'\tilde{\lambda}.$$

Multiplying R from the left, we have:

$$R\tilde{\beta} = R\hat{\beta} + R(X'X)^{-1}R'\tilde{\lambda}.$$

Because $R\tilde{\beta} = r$ has to be satisfied, we have the following expression:

$$r = R\hat{\beta} + R(X'X)^{-1}R'\tilde{\lambda}.$$

Therefore, solving the above equation with respect to $\tilde{\lambda}$, we obtain:

$$\tilde{\lambda} = \left(R(X'X)^{-1}R'\right)^{-1}(r - R\hat{\beta})$$

Substituting $\tilde{\lambda}$ into $\tilde{\beta} = \hat{\beta} + (X'X)^{-1}R'\tilde{\lambda}$, the restricted OLSE is given by:

$$\tilde{\beta} = \hat{\beta} + (X'X)^{-1}R'\left(R(X'X)^{-1}R'\right)^{-1}(r - R\hat{\beta}).$$

(a) The expectation of $\tilde{\beta}$ is:

$$\begin{aligned}
\mathrm{E}(\tilde{\beta}) &= \mathrm{E}(\hat{\beta}) + (X'X)^{-1}R'(R(X'X)^{-1}R')^{-1}(r - R\mathrm{E}(\hat{\beta})) \\
&= \beta + (X'X)^{-1}R'(R(X'X)^{-1}R')^{-1}(r - R\beta) \\
&= \beta,
\end{aligned}$$

because of $R\beta = r$.

Thus, it is shown that $\tilde{\beta}$ is unbiased.

(b) The variance of $\tilde{\beta}$ is as follows.

First, rewrite as follows:

$$
\begin{aligned}
(\tilde{\beta} - \beta) &= (\hat{\beta} - \beta) + (X'X)^{-1}R'\left(R(X'X)^{-1}R'\right)^{-1}(R\beta - R\hat{\beta}) \\
&= (\hat{\beta} - \beta) - (X'X)^{-1}R'\left(R(X'X)^{-1}R'\right)^{-1}(R\hat{\beta} - R\beta) \\
&= (\hat{\beta} - \beta) - (X'X)^{-1}R'\left(R(X'X)^{-1}R'\right)^{-1}R(\hat{\beta} - \beta) \\
&= \left(I_k - (X'X)^{-1}R'\left(R(X'X)^{-1}R'\right)^{-1}R\right)(\hat{\beta} - \beta) \\
&= W(\hat{\beta} - \beta),
\end{aligned}
$$

where $W \equiv I_k - (X'X)^{-1}R'\left(R(X'X)^{-1}R'\right)^{-1}R$.

Then, we obtain the following variance:

$$
\begin{aligned}
\mathrm{V}(\tilde{\beta}) &\equiv \mathrm{E}((\tilde{\beta}-\beta)(\tilde{\beta}-\beta)') = \mathrm{E}(W(\hat{\beta}-\beta)(\hat{\beta}-\beta)'W') \\
&= W\mathrm{E}((\hat{\beta}-\beta)(\hat{\beta}-\beta)')W' = W\mathrm{V}(\hat{\beta})W' = \sigma^2 W(X'X)^{-1}W' \\
&= \sigma^2\Big(I-(X'X)^{-1}R'\big(R(X'X)^{-1}R'\big)^{-1}R\Big)(X'X)^{-1} \\
&\qquad\qquad \times\Big(I-(X'X)^{-1}R'\big(R(X'X)^{-1}R'\big)^{-1}R\Big)' \\
&= \sigma^2(X'X)^{-1} - \sigma^2(X'X)^{-1}R'\big(R(X'X)^{-1}R'\big)^{-1}R(X'X)^{-1} \\
&= \mathrm{V}(\hat{\beta}) - \sigma^2(X'X)^{-1}R'\big(R(X'X)^{-1}R'\big)^{-1}R(X'X)^{-1}
\end{aligned}
$$

That is,

$$
\mathrm{V}(\hat{\beta}) - \mathrm{V}(\tilde{\beta}) = \sigma^2(X'X)^{-1}R'\big(R(X'X)^{-1}R'\big)^{-1}R(X'X)^{-1}
$$

Thus, $\mathrm{V}(\hat{\beta}) - \mathrm{V}(\tilde{\beta})$ is positive definite.

If $X'X$ is positive definite,

$\Longrightarrow$ then $(X'X)^{-1}$ is also positive definite,

$\Longrightarrow$ then $R(X'X)^{-1}R'$ is also positive definite,

$\Longrightarrow$ then $(R(X'X)^{-1}R')^{-1}$ is also positive definite,

$\Longrightarrow$ then $(X'X)^{-1}R'(R(X'X)^{-1}R')^{-1}R(X'X)^{-1}$ is also positive definite,

Let a be a $k \times 1$ vector.

Defining $z = Xa$, which is a $n \times 1$ vector, construct the sum of squared elements $z'z = \sum_{i=1}^{n} z_i^2 > 0$ for $z \neq 0$.

Therefore, we obtain: $z'z = (Xa)'(Xa) = a'X'Xa > 0$ for $z = Xa \neq 0$.

Thus, $X'X$ is positive definite.

3. Another solution:

Again, write the first-order condition for minimization:

$$\frac{\partial L}{\partial \tilde{\beta}} = -2X'(y - X\tilde{\beta}) - 2R'\tilde{\lambda} = 0,$$
$$\frac{\partial L}{\partial \tilde{\lambda}} = -2(R\tilde{\beta} - r) = 0,$$

which can be written as:

$$X'X\tilde{\beta} - R'\tilde{\lambda} = X'y,$$

$$R\tilde{\beta} = r.$$

Using the matrix form:

$$\begin{pmatrix} X'X & R' \\ R & 0 \end{pmatrix} \begin{pmatrix} \tilde{\beta} \\ -\tilde{\lambda} \end{pmatrix} = \begin{pmatrix} X'y \\ r \end{pmatrix}.$$

The solutions of $\tilde{\beta}$ and $-\tilde{\lambda}$ are given by:

$$\begin{pmatrix} \tilde{\beta} \\ -\tilde{\lambda} \end{pmatrix} = \begin{pmatrix} X'X & R' \\ R & 0 \end{pmatrix}^{-1} \begin{pmatrix} X'y \\ r \end{pmatrix}.$$

(*) Formula to the inverse matrix:

$$\begin{pmatrix} A & B \\ B' & D \end{pmatrix}^{-1} = \begin{pmatrix} E & F \\ F' & G \end{pmatrix},$$

where E, F and G are given by:

$$E = (A - BD^{-1}B')^{-1} = A^{-1} + A^{-1}B(D - B'A^{-1}B)^{-1}B'A^{-1}$$

$$F = -(A - BD^{-1}B')^{-1}BD^{-1} = -A^{-1}B(D - B'A^{-1}B)^{-1}$$

$$G = (D - B'A^{-1}B)^{-1} = D^{-1} + D^{-1}B'(A - BD^{-1}B')^{-1}BD^{-1}$$

In this case, E and F correspond to:

$$E = (X'X)^{-1} - (X'X)^{-1}R'\Big(R(X'X)^{-1}R'\Big)^{-1}R(X'X)^{-1}$$

$$F = (X'X)^{-1}R'\Big(R(X'X)^{-1}R'\Big)^{-1}.$$

Therefore, $\tilde{\beta}$ is derived as follows:

$$\begin{aligned}\tilde{\beta} &= EX'y + Fr \\ &= \hat{\beta} + (X'X)^{-1}R'\Big(R(X'X)^{-1}R'\Big)^{-1}(r - R\hat{\beta}).\end{aligned}$$

The variance is:

$$\mathrm{V}\begin{pmatrix} \tilde{\beta} \\ -\tilde{\lambda} \end{pmatrix} = \sigma^2 \begin{pmatrix} X'X & R' \\ R & 0 \end{pmatrix}^{-1}.$$

Therefore, $\mathrm{V}(\tilde{\beta})$ is:

$$\mathrm{V}(\tilde{\beta}) = \sigma^2 E = \sigma^2\Big((X'X)^{-1} - (X'X)^{-1}R'\Big(R(X'X)^{-1}R'\Big)^{-1}R(X'X)^{-1}\Big)$$

Under the restriction: $R\beta = r$,

$$\mathrm{V}(\hat{\beta}) - \mathrm{V}(\tilde{\beta}) = \sigma^2 (X'X)^{-1} R' \Big(R(X'X)^{-1} R' \Big)^{-1} R(X'X)^{-1}$$

is positive definite.