

# Demonstration of the Frisch-Waugh-Lovell (FWL) theorem

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## 1 Multiple Linear Regression Model

Consider the linear regression model:

$$y = X_1\beta_1 + X_2\beta_2 + u \quad (1)$$

Where  $y$  is the vector of outcomes,  $X_1$  is a matrix of regressors of interest,  $X_2$  is a matrix of control variables,  $\beta_1$  and  $\beta_2$  are the coefficient vectors, and  $u$  is the vector of errors.

## 2 Solve for $\hat{\beta}_2$ Estimator

We start by finding the expression for  $\hat{\beta}_2$  in terms of  $\hat{\beta}_1$ , which is derived from multiplying both sides of the equation by  $(X_2'X_2)^{-1}X_2'$ . Solving for  $\hat{\beta}_2$ , we get:

$$\hat{\beta}_2 = (X_2'X_2)^{-1}X_2'y - (X_2'X_2)^{-1}X_2'X_1\hat{\beta}_1 + (X_2'X_2)^{-1}X_2'u \quad (2)$$

Given that the vector of errors is orthogonal to the control variables ( $X_2'u = 0$ ), the last term becomes zero. Therefore, the estimator simplifies to:

$$\hat{\beta}_2 = (X_2'X_2)^{-1}X_2'y - (X_2'X_2)^{-1}(X_2'X_1)\hat{\beta}_1 \quad (3)$$

Note that we use  $\hat{\beta}_1$  instead of  $\beta_1$ , as we are working with the estimators.

## 3 Derivation of the $\hat{\beta}_1$ Estimator

By multiplying both sides of the equation by  $X_1'$ , we have:

$$(X_1'X_1)\hat{\beta}_1 + (X_1'X_2)\hat{\beta}_2 = X_1'y \quad (4)$$

We substitute the expression for  $\hat{\beta}_2$  into this equation:

$$(X_1'X_1)\hat{\beta}_1 + (X_1'X_2) \left[ (X_2'X_2)^{-1}X_2'y - (X_2'X_2)^{-1}(X_2'X_1)\hat{\beta}_1 \right] = X_1'y \quad (5)$$

Expanding and grouping the terms containing  $\hat{\beta}_1$  and  $y$ :

$$(X_1'X_1)\hat{\beta}_1 - (X_1'X_2)(X_2'X_2)^{-1}(X_2'X_1)\hat{\beta}_1 = X_1'y - (X_1'X_2)(X_2'X_2)^{-1}X_2'y \quad (6)$$

Factoring out  $\hat{\beta}_1$  and  $y$ :

$$\left[ (X_1'X_1) - (X_1'X_2)(X_2'X_2)^{-1}(X_2'X_1) \right] \hat{\beta}_1 = \left[ X_1' - (X_1'X_2)(X_2'X_2)^{-1}X_2' \right] y \quad (7)$$

Now we can factor out  $X_1'$  from both sides of the equation and  $X_1$  from the left side. The equation is rewritten as:

$$\left[ X_1'(I - X_2(X_2'X_2)^{-1}X_2')X_1 \right] \hat{\beta}_1 = X_1'(I - X_2(X_2'X_2)^{-1}X_2')y \quad (8)$$

We introduce the matrix  $M_{X_2} = I - X_2(X_2'X_2)^{-1}X_2'$ . Substituting  $M_{X_2}$ :

$$(X_1'M_{X_2}X_1)\hat{\beta}_1 = X_1'M_{X_2}y \quad (9)$$

Solving for  $\hat{\beta}_1$ , we get the OLS (Ordinary Least Squares) estimator for  $\beta_1$ :

$$\hat{\beta}_1 = (X_1'M_{X_2}X_1)^{-1}X_1'M_{X_2}y \quad (10)$$

Given that  $M_{X_2}$  is idempotent we have:

$$\hat{\beta}_1 = (X_1'M_{X_2}'M_{X_2}X_1)^{-1}X_1'M_{X_2}'M_{X_2}y \quad (11)$$

Finally we have:

$$\hat{\beta}_1 = (\tilde{X}_1' \tilde{X}_1)^{-1} \tilde{X}_1' \tilde{y} \quad (12)$$

where  $\tilde{y} = M_{X_2}y$  and  $\tilde{X}_1 = M_{X_2}X_1$