

# Mathematical Proof

## The Frisch-Waugh-Lovell Theorem

### 1 Mathematical Foundation

#### 1.1 Problem Setup

Consider the linear regression model:

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

where the components are defined as follows:

- $y \in \mathbb{R}^{n \times 1}$  is the vector of outcomes
- $X_1 \in \mathbb{R}^{n \times k_1}$  is the matrix of regressors of interest with  $\text{rank}(X_1) = k_1$
- $X_2 \in \mathbb{R}^{n \times k_2}$  is the matrix of control variables with  $\text{rank}(X_2) = k_2$
- $\beta_1 \in \mathbb{R}^{k_1 \times 1}$  is the parameter vector of primary interest
- $\beta_2 \in \mathbb{R}^{k_2 \times 1}$  is the parameter vector for control variables
- $u \in \mathbb{R}^{n \times 1}$  is the error vector with  $\mathbb{E}[u|X_1, X_2] = 0$

**Definition 1.1 (Projection and Annihilator Matrices).** For a full-rank matrix  $X_2 \in \mathbb{R}^{n \times k_2}$ , we define:

$$P_{X_2} = X_2(X_2'X_2)^{-1}X_2' \quad (\text{Projection matrix}) \quad (2)$$

$$M_{X_2} = I_n - P_{X_2} = I_n - X_2(X_2'X_2)^{-1}X_2' \quad (\text{Annihilator matrix}) \quad (3)$$

These matrices satisfy the following fundamental properties:

- (i)  $P_{X_2}$  and  $M_{X_2}$  are symmetric:  $P_{X_2}' = P_{X_2}$ ,  $M_{X_2}' = M_{X_2}$
- (ii)  $P_{X_2}$  and  $M_{X_2}$  are idempotent:  $P_{X_2}^2 = P_{X_2}$ ,  $M_{X_2}^2 = M_{X_2}$
- (iii)  $M_{X_2}X_2 = 0$  and  $P_{X_2}X_2 = X_2$
- (iv)  $P_{X_2} + M_{X_2} = I_n$

## 2 Main Result

### 2.1 The Frisch-Waugh-Lovell Theorem

**Theorem 2.1 (Frisch-Waugh-Lovell Theorem).** The OLS estimate of  $\beta_1$  in the full regression of  $y$  on  $[X_1 \ X_2]$  is identical to the OLS estimate obtained from the following two-step partialling-out procedure:

**Step 1:** Regress  $y$  on  $X_2$  and obtain residuals:  $\tilde{y} = M_{X_2}y$

**Step 2:** Regress  $X_1$  on  $X_2$  and obtain residuals:  $\tilde{X}_1 = M_{X_2}X_1$

**Step 3:** Regress  $\tilde{y}$  on  $\tilde{X}_1$  to obtain:  $\hat{\beta}_1^{\text{FWL}} = (\tilde{X}_1' \tilde{X}_1)^{-1} \tilde{X}_1' \tilde{y}$

**Formal Statement:**

$$\boxed{\hat{\beta}_1 = \hat{\beta}_1^{\text{FWL}} = (\tilde{X}_1' \tilde{X}_1)^{-1} \tilde{X}_1' \tilde{y}} \quad (4)$$

### 2.2 Proof

**Proof.** We establish the equivalence by demonstrating that both approaches yield identical coefficient estimates through rigorous matrix algebra.

#### Part I: Full Regression Setup

The full regression model in partitioned form is:

$$y = [X_1 \ X_2] \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + u = X\beta + u \quad (5)$$

where  $X = [X_1 \ X_2] \in \mathbb{R}^{n \times (k_1 + k_2)}$  and  $\beta = [\beta_1' \ \beta_2']' \in \mathbb{R}^{(k_1 + k_2) \times 1}$ .

The OLS estimator is given by:

$$\hat{\beta} = (X'X)^{-1} X'y = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} \quad (6)$$

#### Part II: Matrix Partitioning

We partition the cross-product matrices:

$$X'X = \begin{bmatrix} X_1'X_1 & X_1'X_2 \\ X_2'X_1 & X_2'X_2 \end{bmatrix} = \begin{bmatrix} A & B \\ B' & D \end{bmatrix} \quad (7)$$

$$X'y = \begin{bmatrix} X_1'y \\ X_2'y \end{bmatrix} \quad (8)$$

where:

$$A = X_1'X_1 \in \mathbb{R}^{k_1 \times k_1}, \quad B = X_1'X_2 \in \mathbb{R}^{k_1 \times k_2}, \quad D = X_2'X_2 \in \mathbb{R}^{k_2 \times k_2} \quad (9)$$

### Part III: Partitioned Matrix Inverse

Using the block matrix inversion formula:

$$(X'X)^{-1} = \begin{bmatrix} (A - BD^{-1}B')^{-1} & -(A - BD^{-1}B')^{-1}BD^{-1} \\ -D^{-1}B'(A - BD^{-1}B')^{-1} & D^{-1} + D^{-1}B'(A - BD^{-1}B')^{-1}BD^{-1} \end{bmatrix} \quad (10)$$

### Part IV: Key Algebraic Identity

We establish the fundamental relationship:

$$A - BD^{-1}B' = X_1'X_1 - X_1'X_2(X_2'X_2)^{-1}X_2'X_1 \quad (11)$$

$$= X_1'(I_n - X_2(X_2'X_2)^{-1}X_2')X_1 \quad (12)$$

$$= X_1'M_{X_2}X_1 \quad (13)$$

### Part V: Extracting $\hat{\beta}_1$

From the normal equations  $(X'X)\hat{\beta} = X'y$ , the first block gives us:

$$\hat{\beta}_1 = (A - BD^{-1}B')^{-1}(X_1'y - BD^{-1}X_2'y) \quad (14)$$

$$= (X_1'M_{X_2}X_1)^{-1}(X_1'y - X_1'X_2(X_2'X_2)^{-1}X_2'y) \quad (15)$$

$$= (X_1'M_{X_2}X_1)^{-1}X_1'(I_n - X_2(X_2'X_2)^{-1}X_2')y \quad (16)$$

$$= (X_1'M_{X_2}X_1)^{-1}X_1'M_{X_2}y \quad (17)$$

### Part VI: Two-Step Procedure Analysis

The partialling-out procedure yields:

$$\tilde{y} = M_{X_2}y \quad (\text{Step 1}) \quad (18)$$

$$\tilde{X}_1 = M_{X_2}X_1 \quad (\text{Step 2}) \quad (19)$$

$$\hat{\beta}_1^{\text{FWL}} = (\tilde{X}_1'\tilde{X}_1)^{-1}\tilde{X}_1'\tilde{y} \quad (\text{Step 3}) \quad (20)$$

### Part VII: Establishing Equivalence

Substituting the definitions from Steps 1 and 2:

$$\hat{\beta}_1^{\text{FWL}} = ((M_{X_2}X_1)'(M_{X_2}X_1))^{-1}(M_{X_2}X_1)'(M_{X_2}y) \quad (21)$$

$$= (X_1'M_{X_2}'M_{X_2}X_1)^{-1}X_1'M_{X_2}'M_{X_2}y \quad (22)$$

### Part VIII: Applying Matrix Properties

Using the symmetry and idempotency of  $M_{X_2}$  from Definition 1.1:

$$M_{X_2}' = M_{X_2} \quad (\text{symmetry}) \quad (23)$$

$$M_{X_2}M_{X_2} = M_{X_2} \quad (\text{idempotency}) \quad (24)$$

Therefore:

$$\hat{\beta}_1^{\text{FWL}} = (X_1'M_{X_2}M_{X_2}X_1)^{-1}X_1'M_{X_2}M_{X_2}y \quad (25)$$

$$= (X_1'M_{X_2}X_1)^{-1}X_1'M_{X_2}y \quad (26)$$

**Part IX: Final Equivalence**

Comparing equations (17) and (26):

$$\hat{\beta}_1 = (X_1' M_{X_2} X_1)^{-1} X_1' M_{X_2} y = \hat{\beta}_1^{\text{FWL}} \quad (27)$$

This establishes the desired result:

$$\boxed{\hat{\beta}_1 = (\tilde{X}_1' \tilde{X}_1)^{-1} \tilde{X}_1' \tilde{y}} \quad (28)$$

□