

**A “projection based” proof of the Frisch-Waugh theorem.**

Consider regression

$$Y = X_1\beta_1 + X_2\beta_2 + e. \quad (1)$$

We will use three useful facts:

1. The best fit to the least squares problem is unique (except, of course, if there is perfect collinearity).
2. Any vector or matrix of variables can be split into its projections. In particular  $X_2 = P_1X_2 + M_1X_2$ . This is something you can ALWAYS do. Here  $P_1$  and  $M_1$  are the projection and residual makers for  $X_1$ . (This is not so surprising because  $M_1 = I - P_1$ .)
3. A regression on orthogonal (sets of) regressors can be done on each (set) at a time while still getting the coefficients from the joint regression.

Now

$$\hat{Y} = X_1\hat{\beta}_1 + X_2\hat{\beta}_2, \quad (2)$$

and, using fact 2, we have

$$\hat{Y} = X_1\hat{\beta}_1 + (P_1X_2 + M_1X_2)\hat{\beta}_2, \quad (3)$$

or, because  $P_1 = X_1(X_1'X_1)^{-1}X_1'$ , we have

$$\hat{Y} = X_1\hat{\gamma}_1 + (M_1X_2)\hat{\beta}_2, \quad (4)$$

where  $\hat{\gamma}_1 = (\hat{\beta}_1 + (X_1'X_1)^{-1}X_1'X_2\hat{\beta}_2)$ . Look at this expression. The fit is the same, so we are still looking at the OLS fit. The fitted coefficients are  $\hat{\gamma}_1$  (the formula for which we don't often make use of) and  $\hat{\beta}_2$  (the original coefficient) to  $M_1X_2$ . Now, use fact 3. Because—by construction— $M_1X_2$  and  $X_2$  are orthogonal, we have that the regression

$$Y = (M_1X_2)\beta_2 + u \quad (5)$$

delivers the same  $\hat{\beta}_2$  as does (5) which is the same  $\hat{\beta}_2$  that comes from the full equation (1). Finally, notice that if you instead regress

$$(M_1Y) = (M_1X_2)\beta_2 + u, \quad (6)$$

you also get the same  $\hat{\beta}_2$ . This comes from fact 2, because  $Y = M_1Y + P_1Y$  and  $P_1Y$  is orthogonal to  $M_1X_2$ , and will drop out in the regression. You may want to use the form (d) to get the same residuals as in (a).