# Observation

The vertical intercept is 53.68715 and the coefficient is 3.533829 for educ. The number of observation is 935 and R2 is 0.2659.

The vertical intercept is 5.973063 and the coefficient is 0.0598392 for educ. The number of observation is 935 and R2 is 0.0974.

The vertical intercept is 5.658288 and the coefficient is 0.0391199 for educ and coefficient for IQ is 0.0058631. The number of observation is 935 and R2 is 0.1297.

We can state δ1 = 3.53, β1 (ii) = 0.0598, β1 (iii) = 0.039 and β2 (iii) = 0.0058631. To verify the equation β1 = β1 + β2 δ1 left side should equal right side. 0.0598392 = 0.0391199 + 0.0058631(3.533829). -> 0.0598392 = 0.0598390, almost the same number. From this we can tell that the coefficient of log(wage) on educ depends on the changes in the coefficients from log(wage) on educ and IQ.

The coefficient on educ is 0.0391199 and the coefficient on IQ is 0.0058631.

(gen x = ln(wage), regress x educ IQ)

The residual variable is -0.8451488.

(regress educ IQ, predict resid, residual, sum residual)

# Conclusion

The vertical intercept is 6.779004 and the residual variable coefficient is 0.0391199. The coefficient is the same from part a. In part one we see the relationship between log(wage) regressed on educ with the relation of IQ and in this function, we can see the relationship between residuals produced between IQ and educ. Then further regressed the residuals with log(wage) to get the same coefficient. Which tells us that the steepness of the function is the same between both regressions.

(regress x resid)

The coefficient determined from the regression of both residuals is the same as before, which is

0.0391199. We can further expand our knowledge about the relationship between multiple regression,

how in a multiple variable regression can have the same coefficient as long as they have one or more

connecting variable. In this case we can see how regression ran independent of one variable can result

into the independent variable coefficient.

(regress x IQ, predict resid1, residual, sum residual, regress resid1 resid)