

# LS 8 Moment Results In Regression

The term moments arose from physics and the tendency of forces creating rotation about a point or axis. The term was introduced by Karl Pearson into statistics

# Results

- **Cov(X,e)=0**

Where X is a predictor and  $e = y - X\beta$

$\text{cov}(X,e) = E[(X - E(X))(e - E(e))]$  (by substitution)

$= E[(X - E(X))((y - X\beta) - E(y - X\beta))]$  (and then by expanding)

$= E[Xy] - E[X^2\beta] - E(Xy) + E(X^2\beta)$

$= 0$

- **$E[e|X]=0$**

By the law of iterated expectations:  $E[e|X] = E[E[Y|X]|X]$

Given that  $e = E[Y|X]$  this simplifies to:  $E[e|X] = E[e|X]$

This implies that  $E[e|X]$  is a constant, and since it's conditioned on X, it must be equal to its expectation, which is 0.

## Results (Cont'd)

- **$E[e]=0$**

This follows directly from the previous result. Since  $E[e|X]=0$  for any value of  $X$ , then  $E[e]=0$

- **If  $g$  is a function of  $X$ , then  $\text{Cov}(g(X),e)=0$**

Using the law of iterated expectations and the properties of conditional expectations:

$$\text{Cov}(g(X),e)=E[g(X)e]-E[g(X)]E[e]$$

Since  $E[e]=0$ , this simplifies to:  $\text{Cov}(g(X),e)=E[g(X)e]$

Now, notice that  $e=E[Y|X]$ , so:  $E[g(X)e]=E[g(X)E[Y|X]]$

By the law of iterated expectations:  $E[g(X)e]=E[E[g(X)Y|X]]$

Since  $g(X)$  is a function of  $X$ , it is constant with respect to  $X$ , and therefore independent of  $Y$  given  $X$ . Hence, we can factor it out of the conditional expectation:  $E[g(X)e]=E[g(X)]E[Y|X]$

Given that  $E[Y|X]=e$  this further simplifies to:  $E[g(X)e]=E[g(X)]e$

Finally, since  $e$  is a constant (a function of  $X$ ), its expectation is itself:  $E[g(X)e]=eE[g(X)]$

Therefore,  $\text{Cov}(g(X),e)=0$

## Results (Cont'd)

- **$V(e|X)=V(Y|X)$**

By the definition of conditional variance:  $V(e|X)=E[(e-E[e|X])^2|X]$

Since  $E[e|X]=0$ , this simplifies to:  $V(e|X)=E[e^2|X]$

Now, notice that  $e=E[Y|X]$  so:  $V(e|X)=E[E[Y^2|X]|X]$

Again, by the law of iterated expectations:  $V(e|X)=E[Y^2|X]$

This is exactly the definition of conditional variance  $V(Y|X)$

- **$V(e)=E[V(Y|X)]$**

By the law of total variance:  $V(e)=E[V(e|X)]+V(E[e|X])$

Since  $V(E[e|X])=0$  (it's a constant),  $V(e)=E[V(e|X)]$

Using the result from point 4, we have:  $V(e)=E[V(Y|X)]$