

5.3 Two numeric covariates

26

Now: two covariates Z, W

Z : numeric

W : numeric

Example: = engine size

= weight

Cars 2004nh

Y = consumption

To start: Both Z and W parameterized
by simple transformation

$$\rightarrow S_Z(z) \in \mathbb{R}^1$$

$$S_W(w) \in \mathbb{R}^1$$

Example

$$S_Z(z) = z$$

$$S_W(w) = \log(w)$$

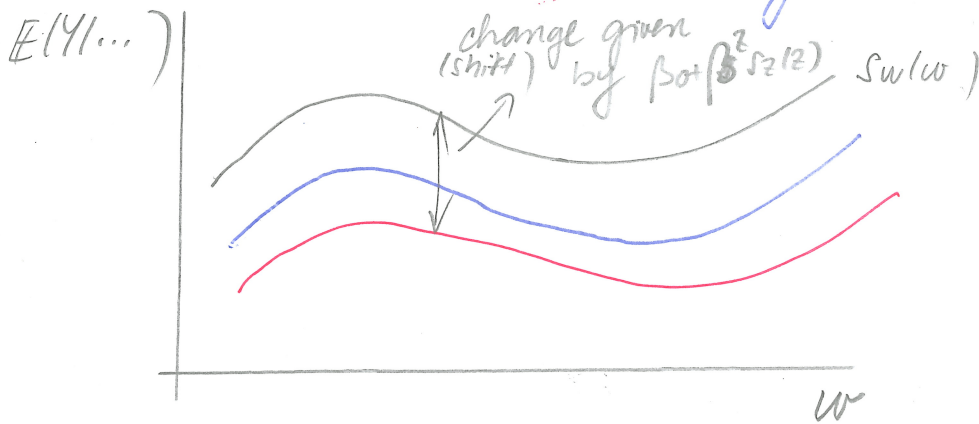
5.3.1 Additivity

MODEL: $E(Y|Z=z, W=w) = m(z, w)$
 $= \beta_0 + \beta^z \cdot s_z(z) + \beta^w \cdot s_w(w)$

Interpretation:

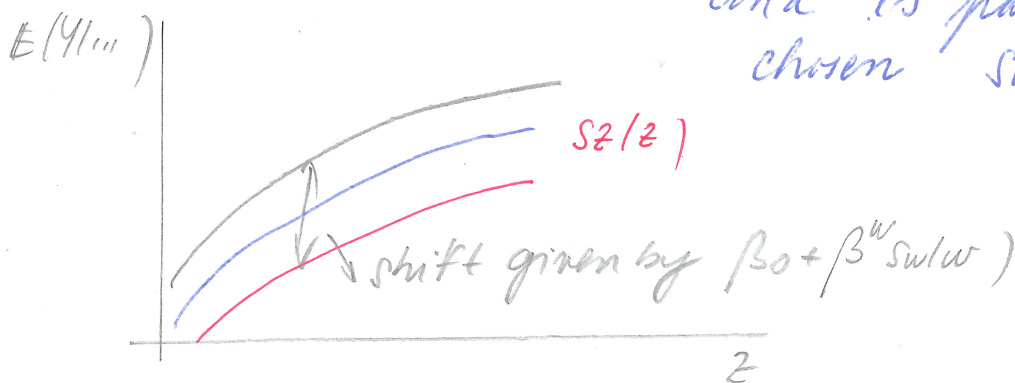
$$E(Y|Z=z, W=w) = \underbrace{\beta_0 + \beta^z s_z(z)}_{\text{intercept}} + \beta^w s_w(w)$$

intercept which depends on z and is parameterized by chosen s_z



$$E(Y|Z=z, W=w) = \underbrace{\beta_0 + \beta^w s_w(w)}_{\text{intercept}} + \beta^z s_z(z)$$

intercept which depends on w and is parameterized by chosen s_w

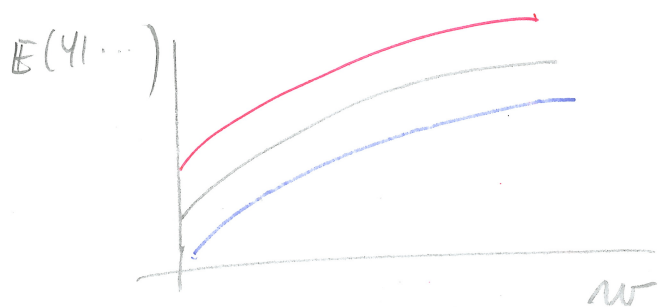


Example

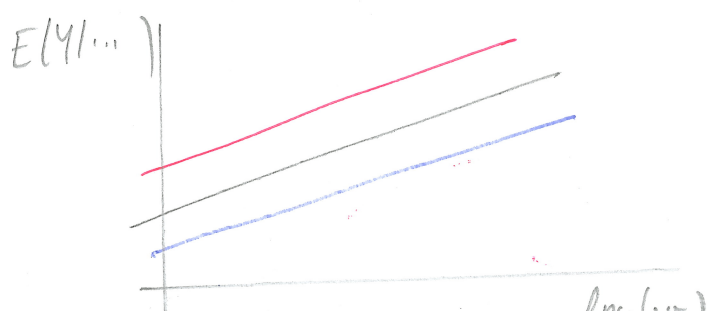
28

$$E(Y|Z=z, W=w) = \beta_0 + \beta^z z + \beta^w \log(w)$$

\uparrow consumption \uparrow engine size \uparrow weight



29



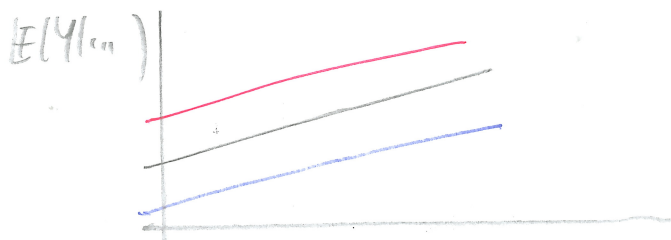
Params. of line in a "group" given by $z=z$:

$$\text{intercept}(z) = \beta_0 + \beta^z z$$

$$\text{slope}(z) = \beta^w \leftarrow \text{does not depend on } z \text{ (additivity assumed)}$$

30

$$E(Y|Z=z, W=w) = \beta_0 + \beta^w \log(w) + \beta^z z$$



31

Params. of line in a "group" z given by $W=w$:

$$\text{intercept}(w) = \beta_0 + \beta^w \log(w)$$

$$\text{slope}(w) = \beta^z \leftarrow \text{does not depend on } w$$

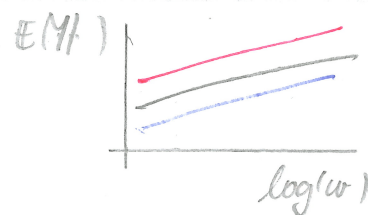
32

5.3. B2 Partial effects

33

Additivity: Effect of Z (or W) on the response expectation does not depend on a value of W (or Z).

MODEL: $E(Y | Z=z, W=w) = \beta_0 + \beta^Z s_Z(z) + \beta^W s_W(w)$



34

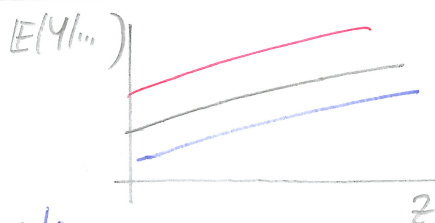
Partial effect of covariate W:

$$E(Y | Z=z, W=w+1) - E(Y | Z=z, W=w) = \beta^W (s_W(w+1) - s_W(w))$$

No effect $\equiv H_0: \beta^W = 0$

\rightarrow t-test on regress. coef.

35



36

Partial effect of covariate z:

$$E(Y | Z=z+1, W=w) - E(Y | Z=z, W=w) = \beta^Z (s_Z(z+1) - s_Z(z))$$

No effect $\equiv H_0: \beta^Z = 0$

\rightarrow t-test on regress. coef.

37

5.3.3 Interactions

$$S_w^T(w) \otimes S_z^T(z) = S_w(w) \cdot S_z(z) =: S_{zw}(z, w)$$

$$\begin{matrix} S_w(w) & \otimes & S_z(z) \\ 1 & & 1 \end{matrix}$$

Interaction model in general

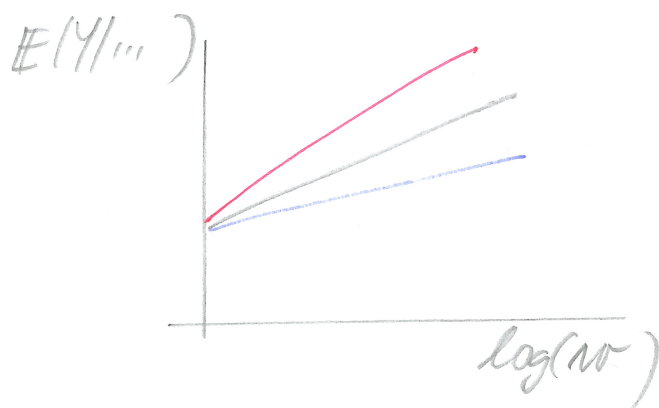
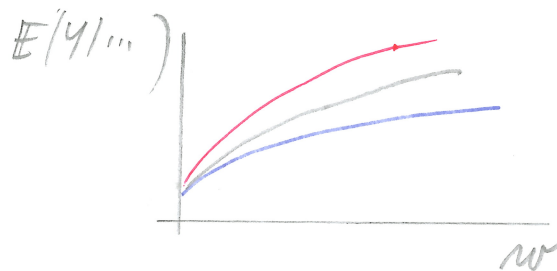
$$E(Y|Z=z, W=w) = \beta_0 + S_z^T(z) \beta^z + S_w^T(w) \beta^w + S_{zw}^T(z, w) \beta^{zw}$$

$$\stackrel{\text{now}}{=} \beta_0 + \beta^z S_z(z) + \beta^w S_w(w) + \beta^{zw} S_z(z) \cdot S_w(w)$$

$$= \underbrace{(\beta_0 + \beta^z S_z(z))}_{\mu_0^w(z)} + \underbrace{(\beta^w + \beta^{zw} S_z(z))}_{\mu_1^w(z)} S_w(w)$$

intercept
depends on z
linearly through $S_z(z)$

slope
depends on z
linearly through $S_z(z)$



Interaction model in general (repetition):

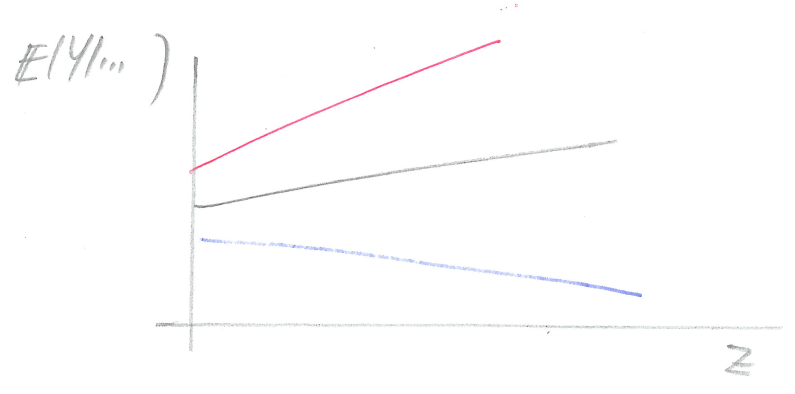
$$E(Y|z=z, W=w) = \beta_0 + S_z^T(z) \beta^z + S_w^T(w) \beta^w + S_{zw}^T(z, w) \beta^{zw}$$

$$\stackrel{NOW}{=} \beta_0 + \beta^z S_z(z) + \beta^w S_w(w) + \beta^{zw} S_z(z) \cdot S_w(w)$$

$$= \underbrace{(\beta_0 + \beta^w S_w(w))}_{\beta_0^z(w)} + \underbrace{(\beta^z + \beta^{zw} S_w(w))}_{\beta_1^z(w)} S_z(z)$$

$\beta_0^z(w)$
intercept depends on w
linearly through $S_w(w)$

$\beta_1^z(w)$
slope depends on w
linearly through $S_w(w)$



Output
- brief discussion
on estimated β 's

5.3.4 Additivity or interactions?

43

Can additivity be assumed?

ASSUMED

$$E(Y|Z=z, W=w) = \beta_0 + \beta^z s_z(z) + \beta^w s_w(w) + \beta^{zw} s_z(z) \cdot s_w(w)$$

$$\rightarrow \beta_0 + \beta^z s_z(z) + \beta^w s_w(w)$$

44-46
plots

$$\underline{H_0: \beta^{zw} = 0} \quad (\text{in interaction model})$$

→ t-test on regression coefficient
or equivalently submodel F-test

t-test on regress. coef.

47

F-test on submodel

48

5.3.5 More complex parameterization of either covariate

- either of the two covariates can (indeed) be parameterized in a more complex way using

$$S_z = (S_z^1, \dots, S_z^{k-1})^T$$

$$S_w = (S_w^1, \dots, S_w^{l-1})^T$$

- polynomials
- splines

Additivity model

$$E(Y|z=z, W=w) = \underbrace{\beta_0 + S_z^T(z)}_{\text{intercept } \mu_0^w(z)} \beta^z + S_w^T(w) \beta^w$$

intercept $\mu_0^w(z)$ which depends on z linearly through $S_z(z)$

$$= \underbrace{\beta_0 + S_w^T(w)}_{\text{intercept } \mu_0^z(w)} \beta^w + S_z^T(z) \beta^z$$

intercept $\mu_0^z(w)$ which depends on w linearly through $S_w(w)$

- role of Z and W can (indeed) be reversed

e.g. $S_z(z) = z$, $S_w(w) = (w, w^2, \dots, w^{l-1})$

$$\mathbb{E}[Y | \underline{z} = z, W = w] = \underbrace{\left(\beta_0 + \sum_{j=1}^{l-1} \beta_j^w w^j \right)}_{\substack{\beta_0^z(w) \text{ through polynomial} \\ \text{in } w}} + \underbrace{\left(\beta^z + \sum_{j=1}^{l-1} \beta_j^{zw} w^j \right)}_{\substack{\beta_1^z(w) \text{ through polynomial} \\ \text{in } w}} \cdot z$$

In general:

- $S_w(w)$ determines on how $\mathbb{E}[Y | z=z, W=w]$ depends on w for fixed (given) z (related coefficients then depend on z linearly through $S_z(z)$)
- $S_z(z)$ determines on how $\mathbb{E}[Y | z=z, W=w]$ depends on z for fixed (given) w (related coefficients then depend on w linearly through $S_w(w)$)