# BOX-TIDWELL TRANSFORMATION REALIZATION WITH R LANGUAGE

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Intro Procedure R Code Conclusion

#### **OVERVIEW**

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## Intro

## PROCEDURE

#### STEP BY STEP PROCEDURE

### Step Zero

$$y = \beta_0 + \beta_1 w_1 + \dots + \beta_k w_k + \epsilon$$
$$w_j = f(x) = \begin{cases} x_j^{\alpha_j} \alpha \neq 0 \\ ln(x_j), \alpha = 0 \end{cases}$$

The method accommodates exponents on one or more of the regressor variables.  $\alpha_1, \alpha_2, \dots, \alpha_k$ 

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## STEP BY STEP PROCEDURE (CONTINUED)

## Step One (Inital Model)

▶ Do a multiple linear regression:

$$E(y_i) = \beta_0 + \beta_1 x_{1i} + \dots + \beta_k x_{ki}$$

We denote the parameter estimates by  $b_0, b_1, \ldots, b_k$ 

- ▶ We can get:  $z_j = x_j ln(x_j)$  which  $x_j$  comes from the original model
- ▶ Do a regression of y on  $x_1, x_2, \ldots, x_k, z_1, z_2, \ldots, z_k$ . Thus estimate  $\gamma_1, \gamma_2, \ldots, \gamma_k$ , the coefficients of the z's. Denote the estimates by  $\hat{\gamma}_1, \hat{\gamma}_2, \ldots, \hat{\gamma}_k$
- ▶ Estimate  $\alpha_1, \alpha_2, \ldots, \alpha_k$  by:

$$\hat{\alpha}_j = \frac{\hat{\gamma}_j}{b_j} + 1 \quad (j = 1, 2, \dots, k)$$

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## STEP BY STEP PROCEDURE (CONTINUED)

#### Step Two (New Model and the Iteration)

The results of equation 6 may be viewd as an updated estimate of  $\alpha_j$ . Often a one step computation is sufficient, in the example below, we do four iterations. Here is the procedure of the iteration model and the how to update the  $\alpha$ :

▶ Use  $w_1^* = x_1^{\hat{\alpha}}, w_2^* = x_2^{\hat{\alpha}} \dots, w_k^* = x_k^{\hat{\alpha}_k}$  to fit the model

$$E(y_i) = \beta_0 + \beta_1 w_1^* + \dots + \beta w_k^*$$

with estimates  $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_k$ 

- ▶ Define  $z_1^* = w_1^* ln(w_1^*), \ z_2 = w_2^* ln(w_2^*), \dots, z_k = w_k^* ln(w_k^*)$
- ▶ Fit a regression of y on  $w_1^*, w_2^*, \ldots, w_k^*, z_1^*, z_2^*, \ldots, z_k^*$  with a new coefficients of  $z_1^*, z_2^*, \ldots, z_k^*$  denoted by  $\hat{\gamma_1}, \hat{\gamma_2}, \ldots, \hat{\gamma_k}$

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## STEP BY STEP PROCEDURE (CONTINUED)

## Step Two (Update Term)

We compute the update  $alpha_j$  with the formula:

$$\hat{\alpha}_j = (\frac{\hat{\gamma}_j}{\hat{\beta}_j} + 1) \times (\text{ Current Value of } \hat{\alpha}_j)$$

We can get the new  $\alpha$  for the new iteration, after n times iterations  $(|(\alpha_{k-1} - \alpha_{k-2}| \leq \epsilon, \epsilon \text{ is the tolrance value})$ , we can stop the iteration and at that time, the  $\alpha$  is what we need: the relative best fitting curve. In multiple regression it can also be a good use of this method, one more variable is to do a set of data loop.

## R Code

#### CODE ONE

```
get.Beta.hat <- function(v.x){
v <- as.matrix(v)
x <- cbind(constant = 1, as.matrix(x))
beta.hat <- solve(t(x)\%*\%x) \%*\% t(x)\%*\%y # (x'x)^-1 * (x'y)
 # Compute standard errors
s2 \leftarrow sum((y - x\%*\%beta.hat)^2)/(nrow(x) - ncol(x))
VCV \leftarrow s2*solve(t(x)%*%x)
SE <- sqrt(diag(VCV))
 # Compute t-values
t <- beta.hat/SE
 # Compute p-values
p <- 2*pt(abs(t),nrow(x) - ncol(x), lower.tail = FALSE)
 # Compute adjusted R-squared
v hat <- x%*%beta.hat
SSr <- sum((y - y_hat)^2)
SSt \leftarrow sum((v - mean(v))^2)
R2 \leftarrow 1 - (SSr/SSt)
adj.R2 \leftarrow 1 - ((1 - R2)*(nrow(x) - 1))/(nrow(x) - ncol(x[,-1]) - 1)
Table <- as.data.frame(round(cbind(beta.hat.SE.t.p. R2), digits = 4))
names(Table)[1:5] <- c("Estimate", "Standard Error", "t-value", "p-value", "R^2")
paste("adi R square is ", adi.R2)
return(list("Table" = Table, "coefficients" = beta.hat, "R2" = R2))
```

#### FIGURE

```
boxtidwell <- function(y,x,tol = .001, max.iter = 25){
 iter <- 1 # the initial iteration
 v <- as.matrix(v)</pre>
 x \leftarrow as.matrix(x)
 w <-x
 alpha <- rep(1, ncol(x)) # initial alpha
 repeat{
   v <- as.matrix(v)
   x \leftarrow as.matrix(x)
   w.log.w <- w*log(w) # alpha
   mod.1 <- get.Beta.hat(y , w)
   mod.2 <- get.Beta.hat(v , cbind(w,w.log.w)) # new model
   alpha <- (mod.2*coefficients[-c(1,2)] / mod.1*coefficients[-1] + 1) * alpha
   print(iter)
   print(alpha)
   if(alpha <= tol || iter >= 4){
     break
   iter <- iter + 1
   for (i in 1:ncol(x)){
     for (j in 1:nrow(x)){
       if(alpha[i] != 0){
         w[i] <- x[i] alpha
       if(alpha[i] == 0){
         w[i] \leftarrow log(x)
 return(list("iter" = iter, "alpha" = alpha))
```

## CONCLUSION

### REFERENCES





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