

# BOX-TIDWELL TRANSFORMATION REALIZATION WITH R LANGUAGE

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# INTRO

# PROCEDURE

## STEP BY STEP PROCEDURE

### Step Zero

$$y = \beta_0 + \beta_1 w_1 + \cdots + \beta_k w_k + \epsilon$$

$$w_j = f(x) = \begin{cases} x_j^{\alpha_j} & \alpha_j \neq 0 \\ \ln(x_j), & \alpha_j = 0 \end{cases}$$

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

## STEP BY STEP PROCEDURE (CONTINUED)

### Step One (Initial Model)

- ▶ Do a multiple linear regression:

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

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

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

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

## STEP BY STEP PROCEDURE (CONTINUED)

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

The results of equation 6 may be viewed as an updated estimate of  $\alpha_j$ . Often a one step computation is sufficient. 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

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

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  $w_1^*, w_2^*, \dots, w_k^*, z_1^*, z_2^*, \dots, z_k^*$  with a new coefficients of  $z_1^*, z_2^*, \dots, z_k^*$  denoted by  $\hat{\gamma}_1, \hat{\gamma}_2, \dots, \hat{\gamma}_k$

## STEP BY STEP PROCEDURE (CONTINUED)

### Step Two (Update Term)

We compute the update  $\hat{\alpha}_j$  with the formula:

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

We can get the new  $\alpha$  for the new iteration, after  $k$  times iterations ( $|\alpha_k - \alpha_{k-1}| \leq \epsilon$ ,  $\epsilon$  is the tolerance 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(y,x){  
  y <- as.matrix(y)  
  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 <- sum((y - x%*%beta.hat)^2)/(nrow(x) - ncol(x))  
  VCV <- 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  
  y_hat <- x%*%beta.hat  
  SSr <- sum((y - y_hat)^2)  
  SSt <- sum((y - mean(y))^2)  
  R2 <- 1 - (SSr/SSt)  
  adj.R2 <- 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("adj R square is ", adj.R2)  
  return(list("Table" = Table, "coefficients" = beta.hat, "R2" = R2))  
}
```

## FIGURE

```

bostidwell <- function(y,x,tol = .001, max.iter = 25){
  iter <- 1 # the initial iteration
  y <- as.matrix(y)
  x <- as.matrix(x)
  w <- x
  alpha <- rep(1, ncol(x)) # initial alpha

  repeat{
    y <- as.matrix(y)
    x <- as.matrix(x)

    w.log.w <- w*log(w) # alpha
    mod.1 <- get.Beta.hat(y , w)
    mod.2 <- get.Beta.hat(y , 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[j] <- x[j]^alpha
        }
        if(alpha[i] == 0){
          w[i] <- log(x)
        }
      }
    }
  }
  return(list("iter" = iter, "alpha" = alpha))
}

```

# CONCLUSION

# REFERENCES



Raymond H.Myers (2005)



Professor.John Fox (2010)

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