#### MSE of Posterior Mean

Kristyn Pantoja

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Bias = 0

 $\mathsf{Bias} \mathrel{\mathop{!}{=}} 0$ 

#### Closed Form MSE of Posterior Mean

For notation, call  $E[\beta|Y] = \beta_n$ .

$$MSE(\beta_n) = Var[\beta_n] + (E[\beta_n] - \beta_T)^2$$
$$= Var[\beta_n] + (E[\beta_n])^2 - 2\beta_T E[\beta_n] + \beta_T^2$$

where

$$Var[\beta_n] = Var\left[\frac{1}{\sigma^2}\Sigma_B(X^Ty + \sigma^2V^{-1}\mu)\right] = Var\left[\frac{1}{\sigma^2}\Sigma_BX^Ty\right]$$

$$= \left(\frac{1}{\sigma^2}\right)^2\Sigma_BX^TVar[y]X\Sigma_B = \left(\frac{1}{\sigma^2}\right)^2\Sigma_BX^T(\sigma^2I)X\Sigma_B$$

$$= \frac{1}{\sigma^2}\Sigma_BX^TX\Sigma_B$$

$$E[\beta_n] = E\left[\frac{1}{\sigma^2}\Sigma_B(X^Ty + \sigma^2V^{-1}\mu)\right] = \frac{1}{\sigma^2}\Sigma_B(X^TE[y] + \sigma^2V^{-1}\mu)$$

$$= \frac{1}{\sigma^2}\Sigma_B(X^TX\beta_T + \sigma^2V^{-1}\mu) = \frac{1}{\sigma^2}\Sigma_BX^TX\beta_T + \Sigma_BV^{-1}\mu$$

where  $\Sigma_B = Var[\beta|Y] = \sigma^2(X^TX + \sigma^2V^{-1})^{-1}$  and  $y \sim N(X\beta_T, \sigma^2I)$ 

## Empirical MSE converges to Closed Form MSE

- ▶ For each parameter  $\beta_i$  in  $\beta = (\beta_1, \dots, \beta_p)^T$ , I calculated the closed form MSE and compare it to the mean empirical MSE.
- First, I consider the case where the bias should be 0, i.e.
  - for the null linear model  $H_0: E[\beta] = \mu_0$  where  $\mu_0 \in \mathbb{R}^3$ , I choose  $\beta_T = \mu_0$
  - and likewise for the alternative quadratic model  $H_1: E[\beta] = \mu_1$  with  $\mu_1 \in \mathbb{R}^5$ , I choose  $\beta_T = \mu_0$ .
- ▶ I look at the values of the closed form MSE and the mean empirical MSE for each parameter  $\beta_i$ , estimated from J simulations. Call them  $MSE(\beta_i)$  and  $MSE_{MC,J}(\beta_i)$  respectively.
- ▶ I also see if, for simulations from 100 to 5000, that the squared difference between the closed from MSE and the mean empirical MSE for  $\beta_i$  goes to 0, i.e.

$$(MSE(\beta_i) - MSE_{MC,J}(\beta_i))^2 \rightarrow 0$$
 as  $J$  gets larger.

▶ And lastly, that the sum of squared differences betwen the closed from MSE and the mean empirical MSE for  $\beta_i$  over all  $\beta_i$  goes to 0, i.e.  $\sum_{i=1}^{p} (MSE(\beta_i) - MSE_{MC,J}(\beta_i))^2 \rightarrow 0$  ▶ note that this is implied if  $(MSE(\beta_i) - MSE_{MC,J}(\beta_i))^2 \rightarrow 0 \ \forall i$ 

#### Bias = 0

#### When Bias = 0

First consider the cases where the Bias<sup>2</sup> term should be 0, i.e.  $\beta_T = \mu_\ell$ , for  $\ell = \{0, 1\}$ .

Here, the number of simulations, J, is 50,000.

## [4] "0.000115239817653859" "0.000322179368423234"

```
# evaluate : if they look stmilar
# HO : muO = betaT = c(0, 0, 0)
as.character(space_closedMSE_v1$closedMSEHO$MSE_postmean)

## [1] "4.9014802470346e-05" "0.000116917258010801" "0.000116917258010801"
as.character(space_EmpMSE_v1$expEmpMSEHO)

## [1] "5.048737256104e-05" "0.000114084758259508" "0.000115239817653859"
# H1 : mu1 = betaT = c(0, 0.2, -0.2, 0.2, -0.2)
as.character(space_closedMSE_v1$closedMSEH1$MSE_postmean)

## [1] "0.000150604774363489" "0.000116917258010808" "0.000326757490453935"
## [4] "0.00016917258010801" "0.000326757490453935"
as.character(space_EmpMSE_v1$expEmpMSEH1)

## [1] "0.000153998948846765" "0.000114084758259508" "0.00032318823464339"
```

# Also note the bias terms are 0 (or very close to 0) in the closed form MSE for $H_0$ and $H_1$ :

```
## HO : mu0 = betaT = c(0, 0, 0)
as.character(space_closedMSE_v1$closedMSEHO$biassq_term)

## [1] "0" "0" "0"

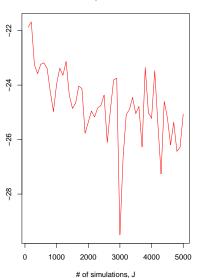
# H1 : mu1 = betaT = c(0, 0.2, -0.2, 0.2, -0.2)
as.character(space_closedMSE_v1$closedMSEH1$biassq_term)

## [1] "2.65898702946963e-32" "6.93889390390723e-18" "6.93889390390723e-18"

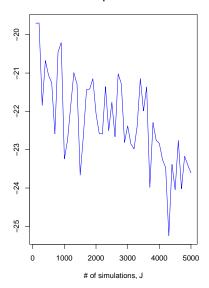
## [4] "0" "6.93889390390723e-18"
```

## Sum of Squared Differences

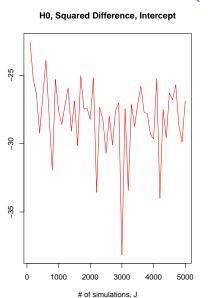
#### **H0 Sum of Squared Differences**



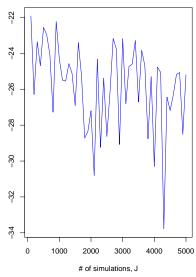
#### H0 Sum of Squared Differences

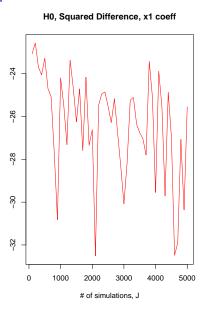


# Squared Differences Beta0 (Intercept)



H1, Squared Difference, Intercept





H1, Squared Difference, x1 coeff -24 -26 -28 -30 -32

1000

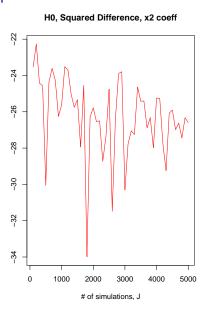
2000

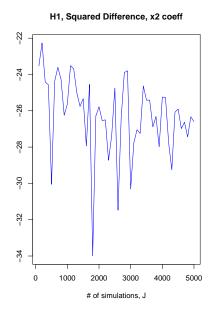
3000

# of simulations, J

4000

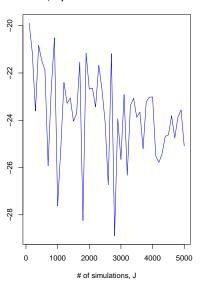
5000



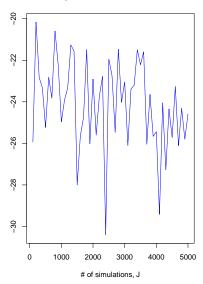


#### Squared Differences for Quadratic Terms x1, x2 in H1

H1, Squared Difference x1^2 coeff



H1, Squared Difference x2^2 coeff



#### Bias != 0

#### When Bias != 0

Here, for assuming a linear model as in  $H_0$ , I set  $\beta_T = (0, 0.7, 0.7)$  and for assuming a quadratic model as in  $H_1$ , I set  $\beta_T = (0, 0.7, -0.7, 0.7 - 0.7)$ . (Again, J = 50,000 in our simulations)

```
# evaluate : if they look similar
# HO : muO = c(0, 0, 0) != betaT
as.character(space_closedMSE_v2$closedMSEH0$MSE_postmean)

## [1] "4.9014802470346e-05" "0.000398156407734911" "0.000398156407734967"
as.character(space_EmpMSE_v2$expEmpMSEH0)

## [1] "4.9369945715031e-05" "0.00040169768581263" "0.000395528969121378"

# H1 : mu1 = c(0, 0.2, -0.2, 0.2, -0.2) != betaT
as.character(space_closedMSE_v2$closedMSEH1$MSE_postmean)

## [1] "0.000956998693917904" "0.000260406620114977" "0.00156575992189813"

## [4] "0.000260406620114922" "0.00156575992189808"
as.character(space_EmpMSE_v2$expEmpMSEH1)
```

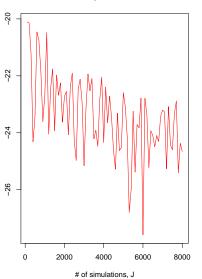
## [1] "0.00097433022286064" "0.000263458157286144" "0.00158612703469216"

## [4] "0.000258028007226336" "0.00158725331520316"

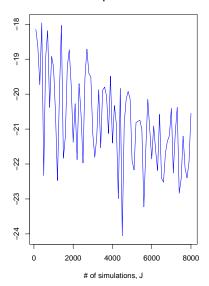
As expected, the bias terms are nonzero in the closed form MSE for  $H_0$  and  $H_1$  in these cases:

## Sum of Squared Differences

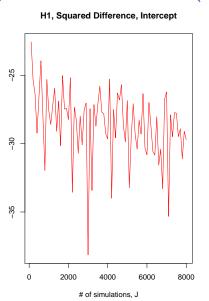
**H0 Sum of Squared Differences** 



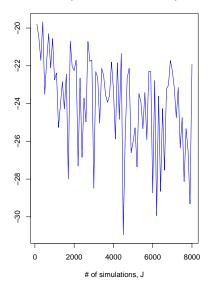
H1 Sum of Squared Differences

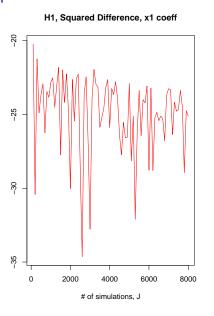


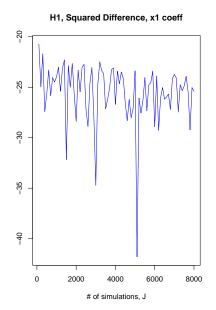
# Squared Differences Beta0 (Intercept)

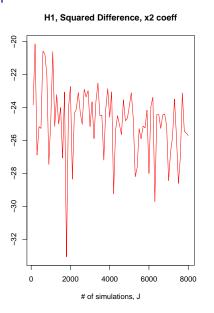


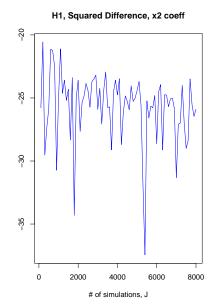
H1, Squared Difference, Intercept





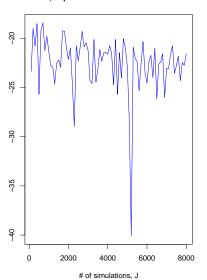






#### Squared Differences for Quadratic Terms x1, x2 in H1

H1, Squared Difference x1^2 coeff



H1, Squared Difference x2^2 coeff

