The Informational Content of Geographical Indications

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Abstract

This file contents the R codes associated with the paper "The informational content of geographical indications" AAWE Working Paper No XXX. The data used are under licence Creative Commons Attribution Share Alike 4.0 International, available on the INRA dataverse website: https://data.inra.fr. Some R functions are reported in the appendix to preserve the visibility of codes. Additional elements and last version of the document are available from https://github.com/jsay/geoInd.

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1 Descriptive Statistics

1.1 Data consistency

Data are available from the github repo, I put them in the folder /Inter

```
library(sp) ; load("Inter/PolyVine.Rda")
Reg.Rank <- subset(PolyVine, PolyVine$PAOC!= 0 &
                   !is.na(PolyVine$DEM) & !is.na(PolyVine$LIBCOM))
Reg.Rank$AOCc <- ifelse(Reg.Rank$GCRU== 1, 5,
                 ifelse(Reg.Rank$PCRU== 1, 4,
                 ifelse(Reg.Rank$VILL== 1 | Reg.Rank$COMM== 1, 3,
                 ifelse(Reg.Rank$BOUR== 1, 2, 1))))
tst <- Reg.Rank@data[, 12: 17]
tst$COMM <- ifelse(tst$VILL== 1 | tst$COMM== 1, 1, 0)
tst$VILL <- 0
table(rowSums(tst), Reg.Rank$AOCc)

tmp <- Reg.Rank$LIBCOM[order(Reg.Rank$YCHF, decreasing= TRUE)]
Reg.Rank$LIBCOM <- factor(Reg.Rank$LIBCOM, levels= unique(tmp))
Reg.Rank$RAYAT <- with(Reg.Rank@data, (SOLAR- mean(SOLAR))/ sd(SOLAR))
Reg.Rank$EXPO <- cut(Reg.Rank$ASPECT,
                     breaks= c(-2, 45, 90, 135, 180, 225, 270, 315, 360))
sapply(Reg.Rank@data, function(x) sum(is.na(x)))
#table(Reg.Old$LIBCOM, Reg.Old$AOCo)
```

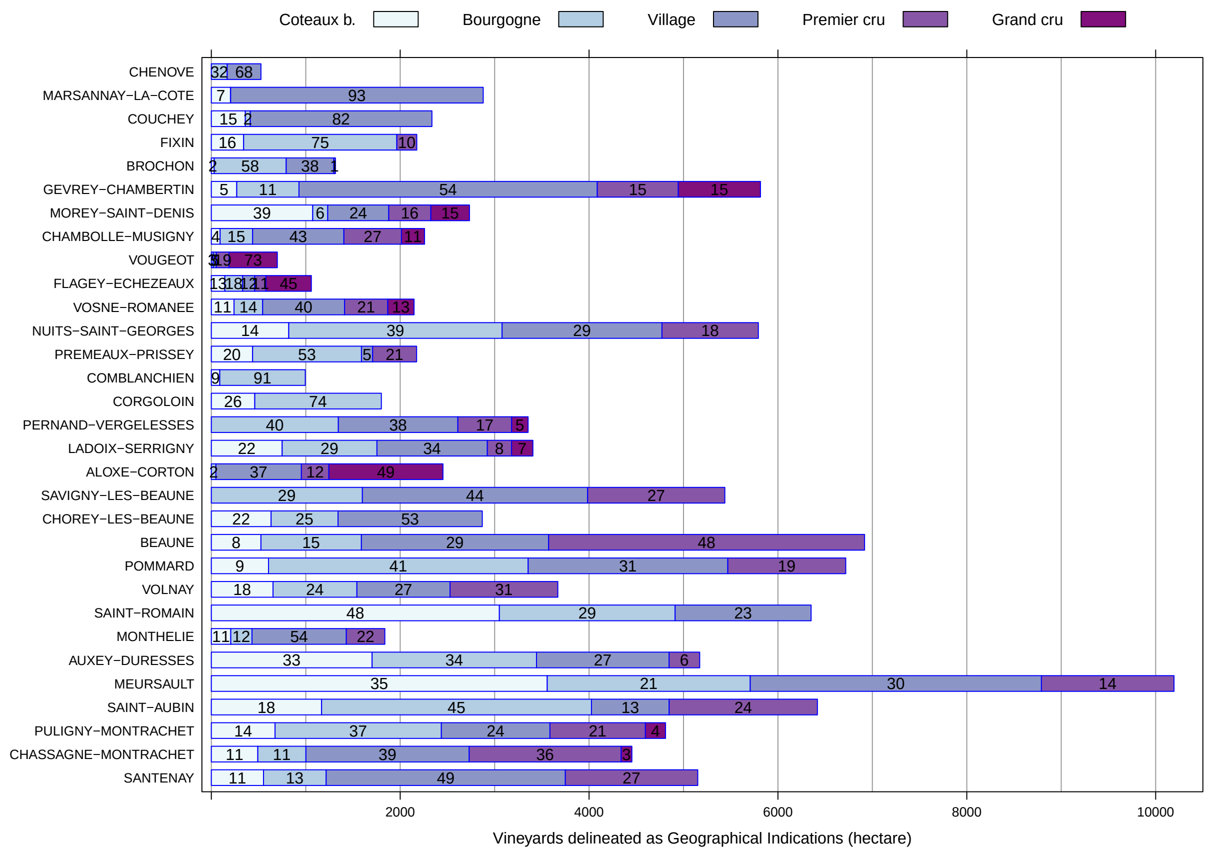
```
       1     2     3     4     5
0    657     0     0     0     0
1   9110   195     0     1     0
2      0 15300     0     1     0
3      0     0 24052    88     0
4      0     0     0  8499     0
5      0     0     0     0  1906

  PAR2RAS        IDU    CODECOM       AREA      PERIM    MAXDIST
        0          0          0          0          0          0
     PAOC       ALIG       BPTG       CREM       MOUS       BGOR
        0          0          0          0          0          0
     BOUR       VILL       COMM       PCRU       GCRU       XL93
        0          0          0          0          0          0
     YL93      NOMOS      URBAN     FOREST      WATER        DEM
        0          0          0          0          0          0
    SLOPE     ASPECT      SOLAR     PERMEA       CODE   NOTATION
        0          0          0          0         22         22
    DESCR  TYPE_GEOL   AP_LOCALE    TYPE_AP   GEOL_NAT   ISOPIQUE
       22         22        102        102         22         22
  AGE_DEB    ERA_DEB    SYS_DEB LITHOLOGIE     DURETE   ENVIRONMT
       22         22         22         22         32         22
```

```
GEOCHIMIE  LITHO_COM       NOUC      NO_UC   NO_ETUDE     SURFUC
       22         32        668        668        668        668
     TARG       TSAB       TLIM     TEXTAG      EPAIS        TEG
      668        668        668        668        668        668
      TMO        RUE        RUD       NOUS      OCCUP     DESCRp
      668        668        668        668        668        668
 AOC36lab   AOC36lvl    LIEUDIT     CLDVIN     LIBCOM       XCHF
       18         18          0          0          0          0
     YCHF     ALTCOM     SUPCOM     POPCOM   CODECANT     REGION
        0          0          0          0          0          0
        X          Y       AOCc      RAYAT       EXPO
        0          0          0          0          0
```

1.2 Crossing GIs dimensions

The interaction between the horizontal (*communes*) and the horizontal (*ranking*) dimension of GIs is assessed through the following Figure, which corresponds to Figure XX in the working paper.

```
library(lattice)
fig.dat <- aggregate(model.matrix(~0+ factor(Reg.Rank$AOCc))*
                     Reg.Rank$AREA/ 1000, by= list(Reg.Rank$LIBCOM), sum)
names(fig.dat) <- c("LIBCOM", "BGOR", "BOUR", "VILL", "PCRU", "GCRU")
fig.dat$LIBCOM <- factor(fig.dat$LIBCOM, levels= rev(levels(fig.dat$LIBCOM)))
fig.crd <- t(apply(fig.dat[, -1], 1, function(t) cumsum(t)- t/2))
fig.lab <- round(t(apply(fig.dat[, -1], 1, function(t) t/ sum(t)))* 100)
barchart(LIBCOM~ BGOR+ BOUR+ VILL+ PCRU+ GCRU, xlim= c(-100, 10500),
         xlab="Vineyards designated as Geographical Indications (hectare)",
         data= fig.dat, horiz= T, stack= T, col= my.pal, border= "blue",
         par.settings= list(superpose.polygon= list(col= my.pal)),
         auto.key= list(space= "top", points= F, rectangles= T, #corner= c(.85, 0.5)
                  columns= 5,
                        text=c("Coteaux b.", "Bourgogne",
                               "Village", "Premier cru", "Grand cru")),
         panel=function(x, y, ...) {
             panel.grid(h= 0, v = -11, col= "grey60")
             panel.barchart(x, y, ...)
             ltext(fig.crd, y,
                   lab= ifelse(fig.lab> 0, fig.lab, ""))}) #paste0(fig.lab, "%")
```



2 Models of GI designation

2.1 Parametric ordered logit

Benchmark parametric ordered logistic model, `por1` corresponds to model (0) of Table XX in the working paper. Model `por1a` is the auxiliary regression used to test the presence of omitted *terroir* effect. Model `por1b` is also an auxiliary regression to compute the Fisher statistics associated to spatial smoothing terms in Table XX.

```
library(MASS)
por1 <- polr(factor(AOCc)~ 0+ LIBCOM+ EXPO
             + poly(DEM, 2)+ poly(SLOPE, 2)+ poly(RAYAT, 2)
             + poly(X, 3)* poly(Y, 3), data= Reg.Rank, Hess= TRUE)
por1a <- polr(factor(AOCc)~ 0 + EXPO
              + poly(DEM, 2)+ poly(SLOPE, 2)+ poly(RAYAT, 2)
              + poly(X, 3)* poly(Y, 3), data= Reg.Rank, Hess= TRUE)
por1b <- polr(factor(AOCc)~ 0+ LIBCOM+ EXPO
              + poly(DEM, 2)+ poly(SLOPE, 2)+ poly(RAYAT, 2)
            , data= Reg.Rank, Hess= TRUE)
```

```
Warning messages:
1: In polr(factor(AOCc) ~ 0 + LIBCOM + EXPO + poly(DEM, 2) + poly(SLOPE,  :
```

```
  une coordonnée à l'origine est nécessaire et assumée
2: In polr(factor(AOCc) ~ 0 + LIBCOM + EXPO + poly(DEM, 2) + poly(SLOPE,  :
  le plan ne semble pas de rang plein, des coefs seront ignorés
```

The warning messages are due to the lack of intercept that we force to compute the ordinal superiority measures for each *communes* below. This has no impact on the quality of the ML estimators.

2.2 Ordered generalized additive

The following code presents 2 loops that allow to estimate the OGAM models of GIs designations. Models (I) to (V) reported in Table XX are only a subset of all models estimated here. The `gamod` object contents the full models, the `gammod` object contents the auxiliary regression to test the omitted *terroir* effects. Because of the complexity of the models, each loop needs about 2 days to run (Dell Precision 7520, 64Go of RAM). I advice the reader to not run the loop entirely but pick some value of `listk` for the maximum degree of freedom and run the models individually. The objects `gamod.Rda` and `gammod.Rda` are available from the git repo mentioned in the first page.

```r
library(mgcv)
listk <- c(50, 100, 200, 300, 400, 500, 600, 700, 800, 900)
gamod <- vector("list", length(listk))
system.time(
for (i in 1: length(listk)){
    gamod[[ i]] <- gam(AOCc~ 0+ LIBCOM+ EXPO+ s(DEM)+ s(SLOPE)+ s(RAYAT)
                       + s(X, Y, k= listk[ i])
                     , data= Reg.Rank, family= ocat(R= 5))
})
names(gamod) <- paste0("gam", listk)
save(gamod, file= "Inter/gamod.Rda")

gammod <- vector("list", length(listk))
system.time(
for (i in 1: length(listk)){
    gammod[[ i]] <- gam(AOCc~ 0+ EXPO+ s(DEM)+ s(SLOPE)+ s(RAYAT)
                        + s(X, Y, k= listk[ i])
                      , data= Reg.Rank, family= ocat(R= 5))
})
names(gammod) <- paste0("gam", listk)
save(gammod, file= "Inter/gammod.Rda")
```

```
utilisateur     système      écoulé
    56177.4       384.9       56565
utilisateur     système      écoulé
    42413.2       262.8     42679.6
```

3 Diagnostics

3.1 Significance

We first reports the Chi-square statistics for the joint significance of the model (0) of Table XX in the working paper.

```
library(car)
res1a <- anova(por1, por1b)
(res1 <- Anova(por1))
```

```
Analysis of Deviance Table (Type II tests)

Response: factor(AOCc)
                          LR Chisq Df Pr(>Chisq)
LIBCOM                       14609 31     <2e-16 ***
EXPO                          1209  7     <2e-16 ***
poly(DEM, 2)                  5308  2     <2e-16 ***
poly(SLOPE, 2)                 400  2     <2e-16 ***
poly(RAYAT, 2)                1934  2     <2e-16 ***
poly(X, 3)                    2484  3     <2e-16 ***
poly(Y, 3)                     647  3     <2e-16 ***
poly(X, 3):poly(Y, 3)         9526  9     <2e-16 ***
---
codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Then, we compute the same statistics for the OGAMs, also reported in Table XX in the main paper.

```
load("Inter/gamod.Rda")
resume <- function(mod){
    tmp <- anova(mod)
    res <- c(as.vector(rbind(tmp$s.table[, 3], tmp$s.table[, 1])),
             as.vector(rbind(tmp$pTerms.tab[, 2], tmp$pTerms.tab[, 1])))
    names(res) <- c(as.vector(rbind(rownames(tmp$s.table), rep("", 4))),
                    as.vector(rbind(rownames(tmp$pTerms.tab), rep("", 2))))
    round(res, 1)
}
sapply(gamod[ 1: 5* 2], resume)
```

```
           gam100  gam300  gam500   gam700   gam900
s(DEM)     5020.2  2385.4  1677.7   1692.6   1766.8
              9.0     8.9     8.8      8.8      8.8
s(SLOPE)   1281.1   458.2   266.1    225.3    243.6
              8.5     8.5     8.5      8.4      8.4
s(RAYAT)   2491.6  1196.5   667.3    554.7    557.9
              8.3     8.2     7.7      7.6      7.5
s(X,Y)    41458.2 73705.5 94094.8 103941.0 107522.8
```

```
            98.7   295.2   483.1    666.7    844.7
LIBCOM    6793.2  6079.7  4594.7   3555.0   2894.5
            31.0    31.0    31.0     31.0     31.0
EXPO       110.3   123.2   222.3    153.5    160.8
             7.0     7.0     7.0      7.0      7.0
```

3.2 Goodness of fit

Here are the goodness-of-fit measures for model (0) also reported in Table XX: McFadden R^2, Akaike information criteria, and percent of good predictions.

```
psR2 <- function(x) 1- (logLik(x)/ logLik(update(x, . ~ + 1)))
round(c(McFaddenR2= psR2(por1), AIC= AIC(por1)/ 1000,
        Pcgp= sum(diag(table(predict(por1), Reg.Rank$AOCc)))/nrow(Reg.Rank)), 2)
```

```
McFaddenR2        AIC       Pcgp
      0.29     119.40       0.59
```

The same goodness of fit measures for OGAMs.

```
pcgp <- function(x){
    sum(diag(table(cut(x$line, c(-Inf, x$family$getTheta(TRUE), Inf)),
                   x$model[, 1])))/ nrow(x$model)* 100
}
rbind(Pcgp= sapply(gamod[ 1: 5* 2], pcgp), AIC= sapply(gamod[ 1: 5* 2], AIC))
#sapply(gamod, psR2)
```

```
       gam100   gam300   gam500   gam700   gam900
Pcgp     73.89    79.94    84.23    86.94    89.15
AIC   82412.10 64710.89 54941.54 48291.33 43535.14
```

3.3 Omitted variable

Bootstrapped statistics for the Fisher about omitted *terroir* variables, with 100 replications for parametric ordered logistic. The absence of correlated effects is strongly rejected. We use the `sure` package for surrogate residual.

```
library(lmtest) ; library(sandwich) ; library(sure)
wal1 <- 0 ; nsim= 100
for (i in 1: nsim){
    tmp <- surrogate(por1a)- por1a$lp
    wal1[ i] <- waldtest(lm(tmp~ Reg.Rank$LIBCOM), . ~ 1, vcov= vcovHC)$F[ 2]
}
quantile(wal1, c(.05, .5, .95))
```

```
   5%   50%   95%
268.0 274.2 279.6
```

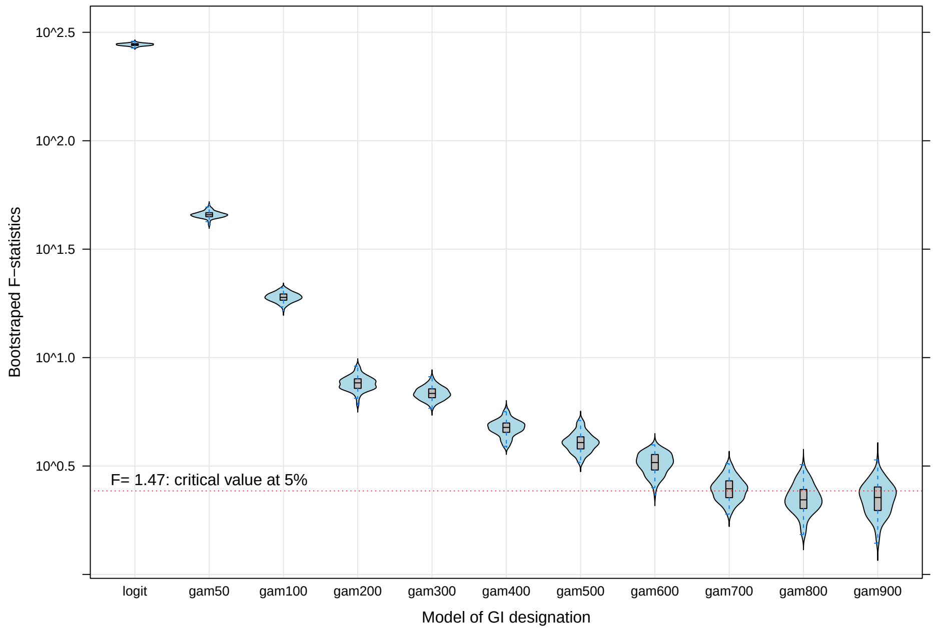
A passer en Reg.Rank, introduire la fonction sur les surrogate residuals des modèles gams en in the Appendix. Not exactly the same because of bootstrap.

```
load("Inter/gammod.Rda") ; source("myFcts.R")
omitVar <- function(mod, var, nsim= 100){
    usq <- 0
    for(i in 1: nsim) {
        RES <- sureOGAM(mod)
        tmp <- lm(I(RES- mod$linear.pred)~ factor(var))
        usq[ i] <- waldtest(tmp, . ~ 1, vcov= vcovHC)$F[ 2]
    }
    usq
}
wal2 <- sapply(gammod, function(x) omitVar(x, RRank$LIBCOM, nsim= 100))
apply(wal2[, 1: 5* 2], 2, function(x) quantile(x, c(.05, .5, .95)))
```

```
    gam100 gam300 gam500 gam700 gam900
5%   17.38  6.060  3.377  2.004  1.704
50%  18.94  6.806  4.130  2.525  2.181
95%  20.15  7.746  4.864  3.060  2.760
```

The following plot resumes the specification diagnostics and shows the relevance of OGAMs to control for omitted spatial effects. It corresponds to Figure XX in the working paper, the bootstrapped nature of the statistics individual values change.

```
library(lattice)
pltdat <- stack(data.frame(logit= wal1, wal2))
bwplot(values~ ind, data= pltdat, type=c("l","g"), horizontal= FALSE,
       xlab='Model of GI designation', ylab='Bootstraped F-statistics',
       par.settings = list(box.rectangle=list(col='black'),
                           plot.symbol = list(pch='.', cex = 0.1)),
       scales=list(y= list(log= TRUE)),
       panel = function(..., box.ratio) {
           panel.grid(h= -1, v = -11)
           panel.violin(..., col = "lightblue",
                        varwidth = FALSE, box.ratio = box.ratio)
           panel.bwplot(..., col='black',
                        cex=0.8, pch='|', fill='gray', box.ratio = .1)
           panel.abline(h= log(1.47), col= "red", lty= 3)
           panel.text(2, log(1.55), "F= 1.47: critical value at 5%")})
```



3.4 Specification

Surrogate residuals can also be used to test specification, results not reported.

```
library(sure) ; library(ggplot2) ; library(gridExtra)
var <- c("DEM", "SLOPE", "RAYAT", "EXPO", "LIBCOM", "X", "Y")
plots <- lapply(var, function(.x)
    autoplot(por1, what= "covariate", x= Reg.Rank@data[, .x], xlab= .x))
do.call(grid.arrange, c(list(autoplot(por1, what= "qq")), plots))
restmp <- sureOGAM(gamod$gam900)- gamod$gam900$line
plot(qlogis(1: nrow(RRank)/ nrow(RRank), scale= 1), sort(restmp))
abline(0, 1)
pltSURE <- function(resid, xvar, lab){
    plot(xvar, resid, xlab= lab, main= paste("Surrogate Analysis", lab))
    abline(h= 0, col= "red", lty= 3, lwd= 2)
    lines(smooth.spline(resid ~ xvar), lwd= 3, col= "blue")
}
par(mfrow= c(3, 3)) ; for (i in var) pltSURE(restmp, RRank@data[, i], i)
```

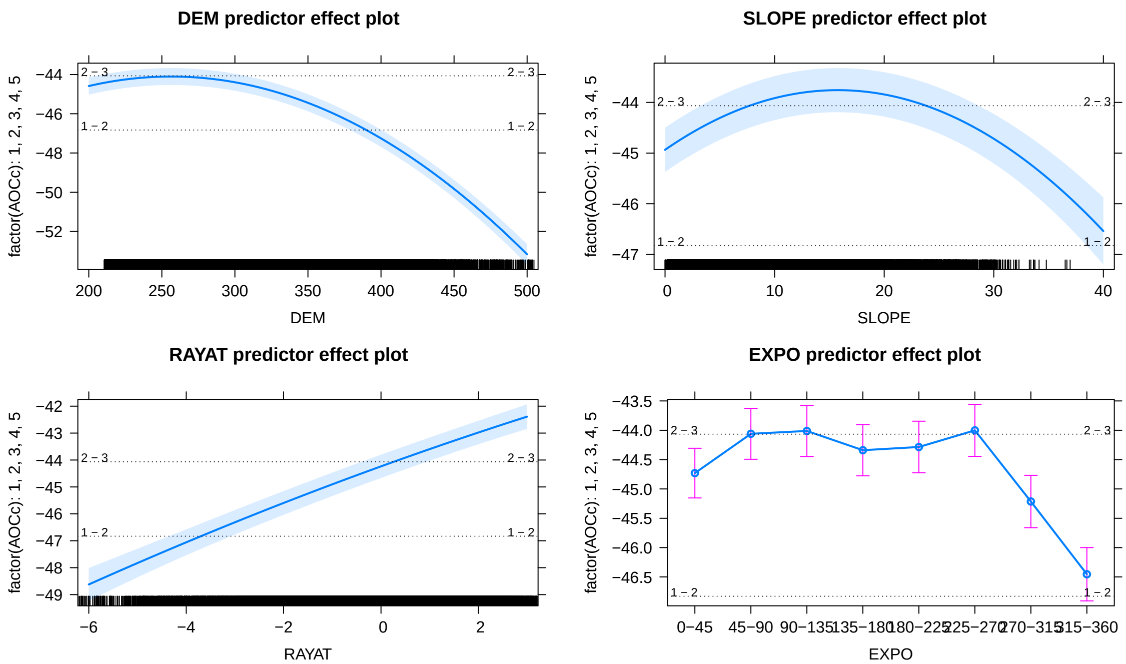
4 Marginal effects

4.1 Parametric ordered logit

Marginal effects from parametric models, corresponds to the dotted lines in Figure XX of the working paper.

```
library(effects)
plot(predictorEffects(por1, ~ DEM+ SLOPE+ RAYAT+ EXPO, latent= TRUE,
                      xlevels=list(DEM= 200: 500,
```

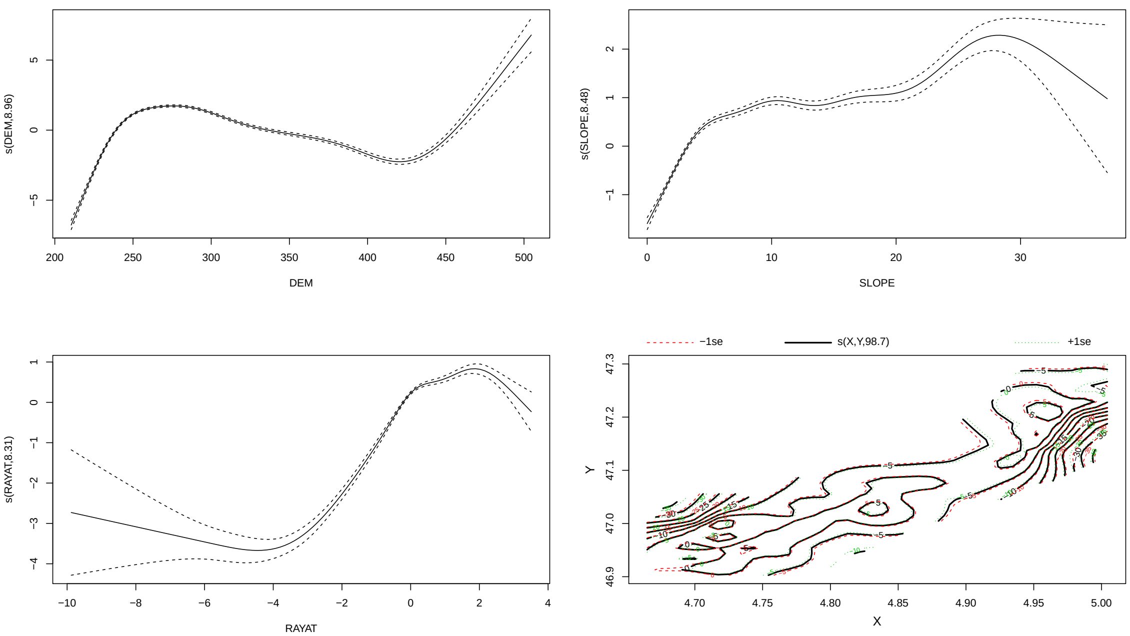
```
SLOPE= 0: 400/ 10, RAYAT= -60: 30/ 10)))
```



4.2 Ordered generalized additive

On voit bien que le lissage est le même que le papier. Can be changed by indexing the list `gamod`, below is the reported effect for a maximum effective degrees of freedom of 100. For all models of `gamod`, we obtain the grey curves of Figure XX of the working paper.

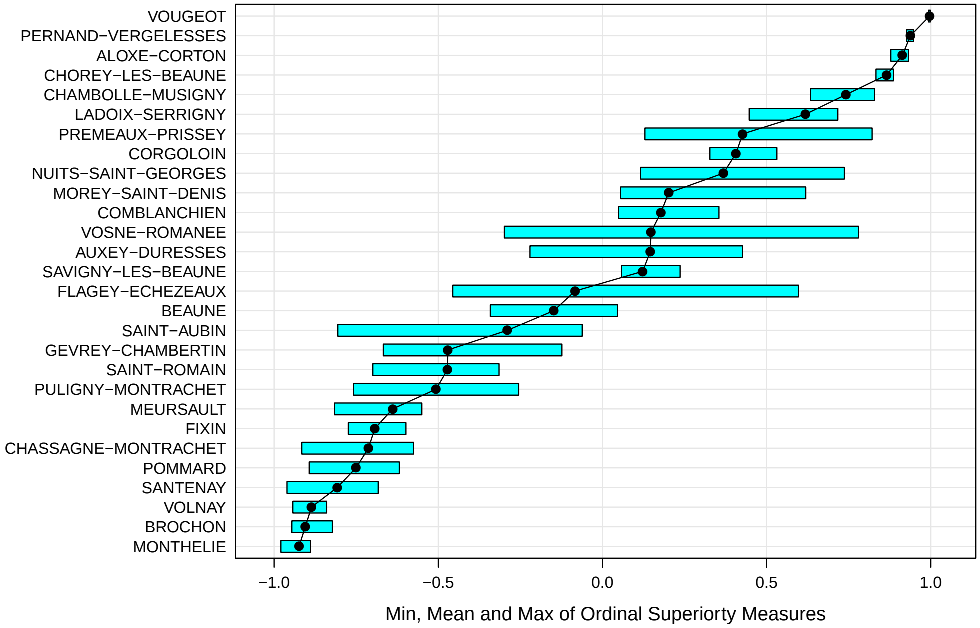
```
plot(gamod[[ 1]], pages= 1, scale= 0)
```



4.3 Ordinal superiority figure

From the equation XX of the working paper, we compute ordinal superiority measures for each OGAMs relatively to the average. It produces the Figure XX of the main text.

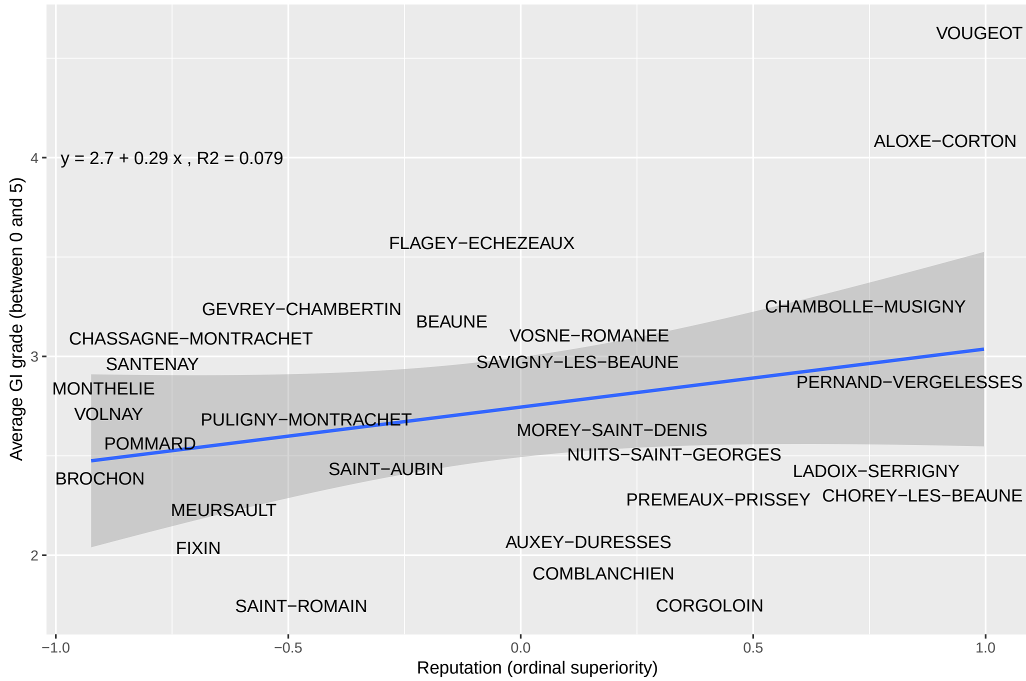
```
library(latticeExtra)
plogi <- function(x) exp(x/ sqrt(2))/ (1+ exp(x/ sqrt(2)))
xx <- data.frame(sapply(gamod, function(x)
    2* plogi(I(x$coeff[ 4: 31]- mean(x$coeff[ 4: 31])))- 1))
ww <- data.frame(xx,
                 LIBCOM= substr(names(gamod[[1]]$coef[ 4: 31]), 7, 30),
                 MIN= apply(xx[ 7: 10], 1, min),
                 MAX= apply(xx[ 7: 10], 1, max),
                 MEAN= apply(xx[ 7: 10], 1, mean))
segplot(reorder(factor(LIBCOM), MEAN)~ MIN+ MAX, length= 5, draw.bands= T,
        data= ww[order(ww$MEAN), ], center= MEAN, type= "o",
        unit = "mm", axis = axis.grid, col.symbol= "black", cex= 1,
        xlab= "Min, Mean and Max of Ordinal Superiorty Measures")
```



4.4 Correlation between *Communes*

Below an unreported Figure to illustrate the claim that "*commune* with higher GIs do not have a preferential treatment" (p.XX) of the working paper. It correlates the average vertical GI score with the ordinal superiority measures from OGAM with XX maximum effective degrees of freedom.

```
library(plyr) ; library(ggrepel)
yy <- ddply(RRank@data, .(LIBCOM),
            function(x) weighted.mean(x$AOCc, x$Area))
zz <- merge(ww, yy, by= "LIBCOM")
m <- lm(V1~ MEAN, data= zz)
a <- signif(coef(m)[1], digits = 2)
b <- signif(coef(m)[2], digits = 2)
c <- signif(summary(m)$r.sq, digits = 2)
textlab <- paste("y = ", a, " + ", b, " x ", ", R2 = ", c, sep= "")
ggplot(zz, aes(MEAN, V1, label= LIBCOM)) +
    geom_smooth(method= lm, aes(MEAN, V1))+
    geom_text_repel(point.padding = NA) +
    annotate("text", x= -.75, y= 4, label= textlab, size= 4, parse= F)+
    xlab("Reputation (ordinal superiority)") +
    ylab("Average GI grade (between 0 and 5)")
```



5 Informational content

5.1 Decomposition table

see appendix for the detailed presentation of the R code to implement the decomposition decompositions. The following code for all OGAMs some computation times, allow the reader to compute the models individually.

```
load("Inter/gamod.Rda") ; source("myFcts.R")
ddtt <- data.frame(AOCc= RRank$AOCc, LIBCOM= RRank$LIBCOM,
                   sapply(gamod[ 1: 5* 2], function(x)
                       rowSums(predict(x, type= 'terms')[, -1])))
dcmp <- sapply(names(ddtt[, 3: 7]), function(x)
    c("Total Signal"= var(ddtt[, x]), "Total Noise"= pi^2/ 3,
      jointSignal(ddtt, x),                      jointNoise(ddtt, x),
      vertiSignal(ddtt, x), vertiResid(ddtt, x), vertiNoise(ddtt, x),
      horizSignal(ddtt, x), horizResid(ddtt, x), horizNoise(ddtt, x)))
round(t(apply(dcmp, 1, function(x) x/ (pi^2/ 3+ dcmp[1, ])* 100)), 1)
```

	gam100	gam300	gam500	gam700	gam900
Signal	84.8	94.7	95.9	96.8	97.6
Noise	15.2	5.3	4.1	3.2	2.4
Joint Signal	68.9	78.5	76.0	77.9	78.7
Joint Noise	16.0	16.2	20.0	18.9	18.9
Rank Signal	55.1	40.3	56.8	61.3	57.6
Rank Residual	13.8	38.2	19.2	16.5	21.2
Rank Noise	29.7	54.4	39.1	35.4	40.0
Com Signal	21.3	37.2	24.6	27.5	29.1

```
Com Residual    47.6    41.3    51.4    50.4    49.7
Com Noise       63.5    57.5    71.3    69.3    68.5
```

6 Models for GIs of 1936

6.1 Descriptive statistics

I present here the detail of the analysis with past GIs, to show that *communes* influences have decreased and informational content has increased since then. It typically makes the same analysis than for actual GIs, first some descriptive statistics.

```
Reg.Old <- subset(Reg.Rank, !is.na(Reg.Rank$AOC36lvl) &
                  !Reg.Rank$LIBCOM %in%
                  c("CHENOVE", "MARSANNAY-LA-COTE", "COUCHEY",
                    "COMBLANCHIEN","CORGOLOIN", "SAINT-ROMAIN"))
Reg.Old$LIBCOM <- factor(Reg.Old$LIBCOM)
Reg.Old$AOCo <- as.numeric(ifelse(Reg.Old$AOC36lvl== "0", 1,
                           ifelse(Reg.Old$AOC36lvl== "3", 2, 3)))
table(Reg.Old$AOC36lvl, Reg.Old$AOCc)
#table(Reg.Old$LIBCOM, Reg.Old$AOCo)
```

```
       1     2     3     4     5
  0  7204 12605  4120   567    39
  3    15   662 15378  8017   261
  5     0     1    13     3  1604
```

6.2 Estimation

The estimation of both the parametric and OGAMs, long computation times for the latter, prefer to fit models individually.

```
library(MASS)
por2 <- polr(factor(AOCo)~ 0+ LIBCOM+ EXPO
             + poly(DEM, 2)+ poly(SLOPE, 2)+ poly(RAYAT, 2)
             + poly(X, 3)* poly(Y, 3), data= Reg.Old, Hess= T)
por2a <- polr(factor(AOCo)~ 0+ EXPO
              + poly(DEM, 2)+ poly(SLOPE, 2)+ poly(RAYAT, 2)
              + poly(X, 3)* poly(Y, 3), data= Reg.Old, Hess= T)
por2b <- polr(factor(AOCo)~ 0+ LIBCOM+ EXPO
              + poly(DEM, 2)+ poly(SLOPE, 2)+ poly(RAYAT, 2)
            , data= Reg.Old, Hess= T)

## A CHANGER WITH NEW DATA
library(mgcv)
listk <- c(50, 75, 100, 150, 200, 250, 300)
gamold <- vector("list", length(listk))
system.time(
for (i in 1: length(listk)){
    gamold[[ i]] <- gam(AOCo~ 0+ LIBCOM+ EXPO+ s(DEM)+ s(SLOPE)+ s(RAYAT)
                        + s(X, Y, k= listk[ i])
```

```
                    , data= Reg.Old, family= ocat(R= 3))
})
names(gamold) <- paste0("gam", listk)
save(gamold, file= "Inter/gamold.Rda")

gammold <- vector("list", length(listk))
system.time(
for (i in 1: length(listk)){
    gammold[[ i]] <- gam(AOCo~ 0+ EXPO+ s(DEM)+ s(SLOPE)+ s(RAYAT)
                        + s(X, Y, k= listk[ i])
                    , data= Reg.Old, family= ocat(R= 3))
})
names(gammold) <- paste0("gam", listk)
save(gammold, file= "Inter/gammold.Rda")
```

```
utilisateur      système       écoulé
    12259.5        144.1      12405.5
utilisateur      système       écoulé
    9582.37        78.69      9661.62
```

6.3 Significance

Significance of all models of GIs designation, corresponds to Table XX in Appendix of the working paper.

```
load("Inter/gamold.Rda")
res2a <- anova(por2, por2b)
res2 <- Anova(por2)
sapply(gamold[ 3: 7], resume)
```

```
            gam100  gam150  gam200  gam250  gam300
s(DEM)       499.8   647.4   702.3   541.9   344.5
               8.5     8.2     8.8     8.4     7.7
s(SLOPE)     387.3   314.0   254.4   244.3   153.0
               8.7     8.7     8.6     8.6     8.3
s(RAYAT)     242.0   160.1   127.1   122.9   105.2
               8.5     8.3     8.1     5.0     5.9
s(X,Y)     17520.5 20194.2 22301.7 23507.2 23801.4
              98.3   146.3   194.4   239.8   286.6
LIBCOM      2782.5  1843.0  1642.4  1283.0  1049.4
              25.0    25.0    25.0    25.0    25.0
EXPO         119.8    91.8    91.9    96.1    90.2
               7.0     7.0     7.0     7.0     7.0
```

6.4 Goodness of fit

Goodness of fit measures from the same Table XX in Appendix.

```
round(c(McFaddenR2= psR2(por2), AIC= AIC(por2)/ 1000,
        Pcgp= sum(diag(table(predict(por2), Reg.Old$AOCo)))/ nrow(Reg.Old)), 2)
rbind(Pcgp= sapply(gamold, pcgp), AIC= sapply(gamold, AIC))
#sapply(gamold, psR2)
```

```
McFaddenR2        AIC       Pcgp
      0.38      51.29       0.79
        gam50    gam75    gam100    gam150    gam200   gam250    gam300
Pcgp     84.34     85.9     87.08     89.26     90.28     91.4     92.54
AIC   40789.58 36833.3 33810.36 30271.01 27574.12 24526.6 22482.20
```

6.5 Omitted variable

Bootstrapped statistics for omitted variables, not reported in the working paper, mentioned at p.XX, .

```
library(lmtest) ; library(sandwich) ; library(sure)
wal3 <- 0 ; nsim= 100
for (i in 1: nsim){
    tmp <- surrogate(por2a)- por2a$lp
    wal3[ i] <- waldtest(lm(tmp~ Reg.Old$LIBCOM), . ~ 1, vcov= vcovHC)$F[ 2]
}
load("Inter/gammold.Rda") ; source("myFcts.R")
wal4 <- sapply(gammold, function(x) omitVar(x, SRank$LIBCOM, nsim= 100))
wold <- data.frame(logit= wal3, wal4)
apply(wold, 2, function(x) quantile(x, c(.05, .5, .95)))
```

```
    logit gam50  gam75 gam100 gam150 gam200 gam250 gam300
5%  168.1 7.408  7.340  4.714  3.498  2.057  1.178  1.091
50% 173.6 8.553  8.843  5.894  4.310  2.709  1.832  1.488
95% 179.8 9.958 10.501  6.858  5.396  3.851  2.495  2.057
```

The same plot as for current GIs, same evidences about the relevance of spatial smoothing terms, the non significance is reach for smaller degrees of freedom (p.XX)

```
library(lattice)
poldat <- stack(wold)
bwplot(values~ ind, data= poldat, type=c("l","g"), horizontal= FALSE,
       xlab='Model of GI designation', ylab='Bootstraped F-statistics',
       par.settings = list(box.rectangle=list(col='black'),
                           plot.symbol = list(pch='.', cex = 0.1)),
       scales=list(y= list(log= TRUE)),
       panel = function(..., box.ratio) {
           panel.grid(h= -1, v = -11)
           panel.violin(..., col = "lightblue",
                        varwidth = FALSE, box.ratio = box.ratio)
           panel.bwplot(..., col='black',
                        cex=0.8, pch='|', fill='gray', box.ratio = .1)
           panel.abline(h= log(1.47), col= "red", lty= 3)
           panel.text(2, log(1.55), "F= 1.47: critical value at 5%")})
```

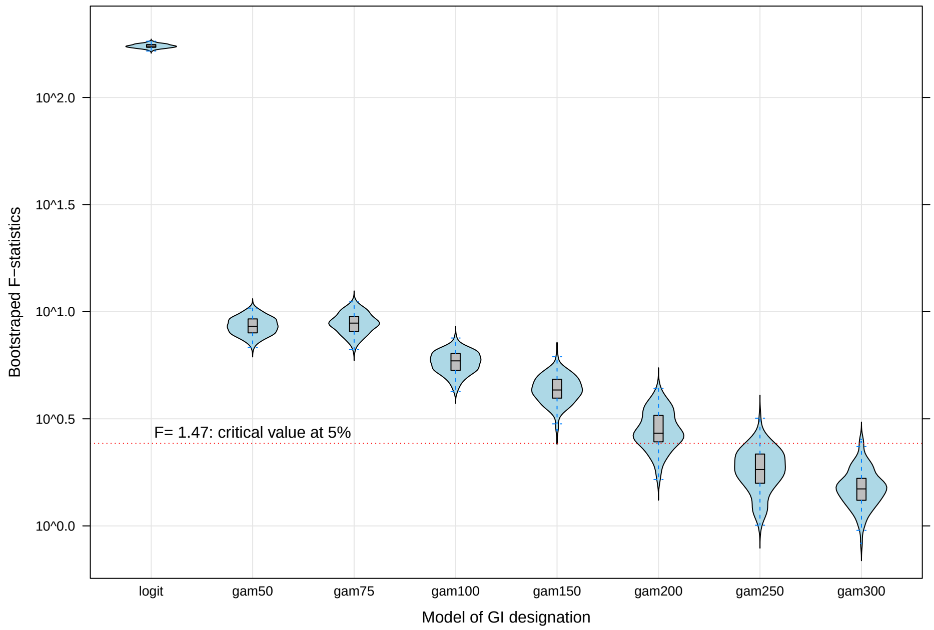


Figure 1: Effects of model XX

6.6 Specification

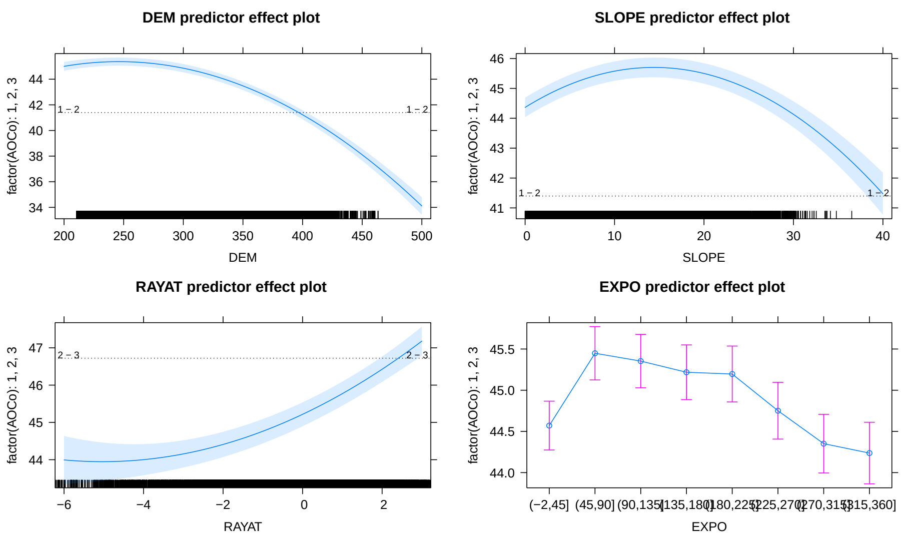
results not reported, parler de ce qu'il se passe moins bien mais qui n'est pas grave. Dans le gam 300 il y a un point qui fait n'imp, probablement un trou dans la carte de Florian.

```
library(sure) ; library(ggplot2) ; library(gridExtra)
var <- c("DEM", "SLOPE", "RAYAT", "EXPO", "LIBCOM", "X", "Y")
plots <- lapply(var, function(.x)
    autoplot(por2, what= "covariate", x= Reg.Old@data[, .x], xlab= .x))
do.call(grid.arrange, c(list(autoplot(por2, what= "qq")), plots))

restmp <- sureOGAM(gamold$gam300)- gamold$gam300$line
plot(qlogis(1: nrow(SRank)/ nrow(SRank), scale= 1), sort(restmp))
abline(0, 1)
var <- c("DEM", "SLOPE", "RAYAT", "EXPO", "LIBCOM", "X", "Y")
par(mfrow= c(3, 3)) ; for (i in var) pltSURE(restmp, SRank@data[, i], i)
```

6.7 Marginal effects

Marginal effect ca be assessed, corresponds to Figure XX in the appendix in the working paper.

```
library(effects)
plot(predictorEffects(por2, ~ DEM+ SLOPE+ RAYAT+ EXPO, latent= TRUE,
                      xlevels=list(DEM= 200: 500,
                                   SLOPE= 0: 400/ 10, RAYAT= -60: 30/ 10)))
plot(gamold$gam300, pages= 1, scale= 0)
```



6.8 Ordinal superiority

Ordinal superiority of *commune* from the GIs of 1936, same equation XX of the working paper and Figure XX in the appendix.

```
xxx <- data.frame(sapply(gamold, function(x)
    2* plogi(I(x$coeff[ 1: 25]- mean(x$coeff[ 1: 25])))- 1))
www <- data.frame(xxx,
                  LIBCOM= substr(names(gamold[[ 1]]$coef[ 1: 25]), 7, 30),
                  MIN= apply(xxx[ 6: 7], 1, min),
                  MAX= apply(xxx[ 6: 7], 1, max),
                  MEAN= apply(xxx[ 6: 7], 1, mean))
segplot(reorder(factor(LIBCOM), MEAN)~ MIN+ MAX, length= 5, draw.bands= T,
        data= www[order(www$MEAN), ], center= MEAN, type= "o",
        unit = "mm", axis = axis.grid, col.symbol= "black", cex= 1,
        xlab= "Min, Mean and Max of Ordinal Superiorty Measures")
```

6.9 Correlation between models

An additional unreported Figure to show the claim that "the importance of *communes* has decreased since the 1936 scheme" (p.XX)

```
zzz <- merge(ww, www, by= "LIBCOM")
segplot(reorder(factor(LIBCOM), MEAN.x)~ MEAN.y+ MEAN.x, data= zzz,
        segments.fun = panel.arrows, length = 2, unit = "mm",
        draw.bands= F, axis = axis.grid,
        xlab= "Rate of variation for ordinal superiority")
```

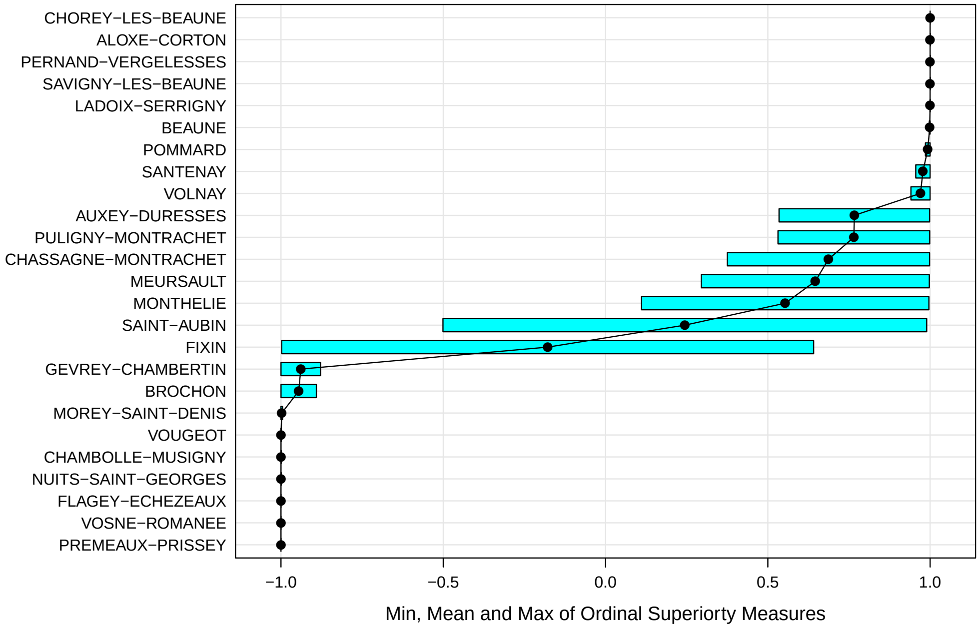
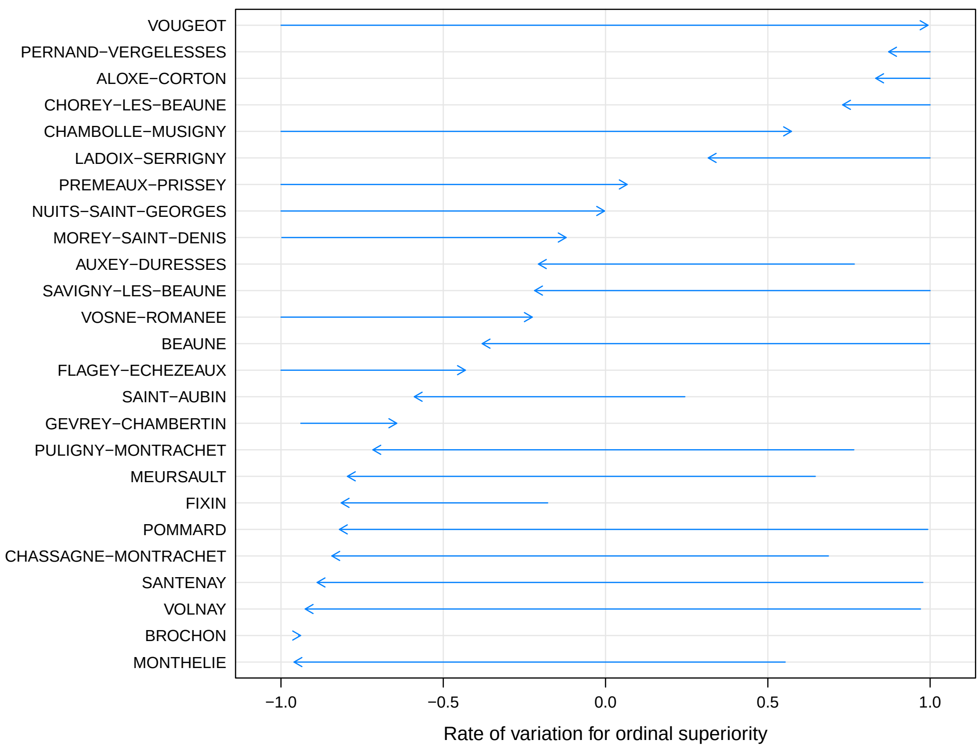


Figure 2: Effects of model XX



6.10 Decomposition table

And then the decomposition table unreported in the main text that show the "smaller joint informational content of GIs in 1936" (p.XX).

```
load("Inter/gamold.Rda") ; source("myFcts.R")
ddoo <- data.frame(AOCavt= SRank$AOCavt, LIBCOM= SRank$LIBCOM,
                   sapply(gamold, function(x)
                       rowSums(predict(x, type= 'terms')[, -1])))
dcop <- sapply(names(ddoo[, 3: 9]), function(x)
    c("Total Signal"= var(ddoo[, x]), "Total Noise"= pi^2/ 3,
      jointSignal(ddoo, x, "AOCavt"), jointNoise(ddoo, x, "AOCavt"),
      vertiSignal(ddoo, x, "AOCavt"), vertiResid(ddoo, x, "AOCavt"), vertiNoise(ddoo, x, "AOCavt"),
      horizSignal(ddoo, x, "AOCavt"), horizResid(ddoo, x, "AOCavt"), horizNoise(ddoo, x, "AOCavt")))
round(t(apply(dcop, 1, function(x) x/ (pi^2/ 3+ dcop[1, ])* 100)), 1)
```

	gam50	gam75	gam100	gam150	gam200	gam250	gam300
Signal	95.6	93.1	95.4	98.7	98.1	99.5	99.5
Noise	4.4	6.9	4.6	1.3	1.9	0.5	0.5
Joint Signal	78.7	63.2	55.3	75.2	47.9	75.0	45.1
Joint Noise	16.9	29.9	40.2	23.5	50.3	24.5	54.5
Rank Signal	5.8	18.1	24.1	16.4	20.6	14.9	22.7
Rank Noise	89.8	75.0	71.3	82.4	77.5	84.6	76.8
Rank Residual	72.9	45.1	31.2	58.8	27.3	60.1	22.4
Com Signal	67.5	39.6	29.4	62.3	24.0	62.7	22.6
Com Noise	28.1	53.5	66.0	36.4	74.1	36.8	77.0
Com Residual	16.0	33.3	43.7	20.9	35.3	20.6	43.7

7 Alternative GI designations

7.1 Change latent vineyard quality

We conclude this work with the simulations of alternative GIs designations schemes. Below are scenarios XX from XX, need to run the code. Put the equations here.

```
load("Inter/gamod.Rda")
prdd <- predict(gamod$gam900, type= 'terms')
thsld <- c(-Inf, gamod$gam900$family$getTheta(TRUE), Inf)
ltt0 <- rowSums(prdd)- (sureOGAM(gamod$gam900)- gamod$gam900$line)
ltt1 <- rowSums(prdd)
ltt2 <- mean(prdd[, 1])+ rowSums(prdd[, -1])-
    (sureOGAM(gamod$gam900)- gamod$gam900$line)
ltt3 <- mean(prdd[, 1])+ rowSums(prdd[, -1])
## CHANGER RRank$AOCavt
Simu <- data.frame(RRank, ltt= rowSums(prdd[, -1]),
                   OLD= RRank$AOCavt, S0= cut(ltt0, thsld),
                   SI= cut(ltt1, thsld), SII= cut(ltt2, thsld),
                   SIII= cut(ltt3, thsld))
table(Simu$AOCc, Simu$S0) ; table(Simu$AOCc, Simu$SI)
table(Simu$AOCc, Simu$SII) ; table(Simu$AOCc, Simu$SIII)
```

```
               OLD  CF1  CF2  CF3  CF4  CF5  CF6
Signal         97.1 97.1 97.1 97.1 97.1 97.1 97.1
Noise           2.9  2.9  2.9  2.9  2.9  2.9  2.9
Joint Signal   51.4 80.1 81.2 82.2 79.4 80.0 79.2
Joint Noise    45.8 17.1 15.9 15.0 17.7 17.1 18.0
Rank Signal    38.9 70.7 64.5 73.5 62.2 62.8 62.0
Rank Noise     58.2 26.4 32.6 23.6 34.9 34.3 35.1
Rank Residual  12.5  9.4 16.7  8.7 17.2 17.2 17.2
Com Signal     28.5 28.5 28.5 28.5 28.5 28.5 28.5
Com Noise      68.6 68.6 68.6 68.6 68.6 68.6 68.6
Com Residual   22.9 51.6 52.7 53.7 50.9 51.5 50.7
```

7.2 Add a vertical level in GIs

Below are the simulations from scenarios XX, XX, and XX, according to changing XX. Put the equations here.

```r
thrldBOUR <- mean(ltt0[RRank$AOCc== 2])
thrldVILL <- mean(ltt0[RRank$AOCc== 3])
thrldPCRU <- mean(ltt0[RRank$AOCc== 4])
Simv <- data.frame(Simu,
                    SIV= ifelse(RRank$AOCc< 2, RRank$AOCc,
                         ifelse(RRank$AOCc== 2 & ltt0< thrldBOUR, 2,
                         ifelse(RRank$AOCc== 2 & ltt0>= thrldBOUR, 3,
                                RRank$AOCc+ 1))),
                    SV = ifelse(RRank$AOCc< 3, RRank$AOCc,
                         ifelse(RRank$AOCc== 3 & ltt0< thrldVILL, 3,
                         ifelse(RRank$AOCc== 3 & ltt0>= thrldVILL, 4,
                                RRank$AOCc+ 1))),
                    SVI= ifelse(RRank$AOCc< 4, RRank$AOCc,
                         ifelse(RRank$AOCc== 4 & ltt0< thrldPCRU, 4,
                         ifelse(RRank$AOCc== 4 & ltt0>= thrldPCRU, 5,
                                RRank$AOCc+ 1))))
table(Simv$AOCc, Simv$SIV)
table(Simv$AOCc, Simv$SV) ; table(Simv$AOCc, Simv$SVI)
```

```
        1     2     3     4     5     6
  1  9759     0     0     0     0     0
  2     0  8931  6577     0     0     0
  3     0     0     0 24151     0     0
  4     0     0     0     0  8577     0
  5     0     0     0     0     0  1906

        1     2     3     4     5     6
  1  9759     0     0     0     0     0
  2     0 15508     0     0     0     0
```

```
3     0     0 13275 10876     0     0
4     0     0     0     0  8577     0
5     0     0     0     0     0  1906

      1     2     3     4     5     6
1  9759     0     0     0     0     0
2     0 15508     0     0     0     0
3     0     0 24151     0     0     0
4     0     0     0  4970  3607     0
5     0     0     0     0     0  1906
```

7.3 Decomposition table

And the decomposition Table which corresponds to Table XX in the working paper.

```
decf <- sapply(names(Simv[, 100: 107]), function(x)
    c("Total Signal"= var(Simv[, "ltt"]), "Total Noise"= pi^2/ 3,
      jointSignal(Simv, "ltt", vt= x), jointNoise(Simv, "ltt", vt= x),
      vertiSignal(Simv, "ltt", vt= x), vertiResid(Simv, "ltt", vt= x), vertiNoise(Simv, "ltt", vt= x),
      horizSignal(Simv, "ltt", vt= x), horizResid(Simv, "ltt", vt= x), horizNoise(Simv, "ltt", vt= x)))
round(t(apply(decf, 1, function(x) x/ (pi^2/ 3+ decf[1, ])* 100)), 1)
```

```
                     OLD   S0   SI  SII SIII  SIV   SV  SVI
Total Signal        97.6 97.6 97.6 97.6 97.6 97.6 97.6 97.6
Total Noise          2.4  2.4  2.4  2.4  2.4  2.4  2.4  2.4
Joint Signal        50.7 78.4 80.7 81.1 82.8 79.2 79.7 79.0
Joint Noise         46.9 19.2 16.8 16.5 14.8 18.4 17.9 18.6
Vertical Signal     35.9 56.8 59.8 70.7 73.1 58.1 58.5 58.0
Vertical Residual   14.9 21.6 21.0 10.4  9.7 21.1 21.2 21.1
Vertical Noise      61.7 40.8 37.8 26.9 24.5 39.4 39.1 39.6
Horizontal Signal   29.1 29.1 29.1 29.1 29.1 29.1 29.1 29.1
Horizontal Residual 21.6 49.3 51.7 52.0 53.7 50.1 50.6 50.0
Horizontal Noise    68.5 68.5 68.5 68.5 68.5 68.5 68.5 68.5
```

8 Session information

```
sessionInfo()
```

```
R version 3.5.3 (2019-03-11)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 18.04.2 LTS

Matrix products: default
BLAS: /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.7.1
LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.7.1

locale:
 [1] LC_CTYPE=fr_FR.UTF-8       LC_NUMERIC=C
 [3] LC_TIME=fr_FR.UTF-8        LC_COLLATE=fr_FR.UTF-8
 [5] LC_MONETARY=fr_FR.UTF-8    LC_MESSAGES=fr_FR.UTF-8
 [7] LC_PAPER=fr_FR.UTF-8       LC_NAME=C
 [9] LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=fr_FR.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] stats4    stats     graphics  grDevices utils     datasets
[7] methods   base

other attached packages:
 [1] gridExtra_2.3      xtable_1.8-3       ggrepel_0.8.0
 [4] ggplot2_3.1.0      plyr_1.8.4         latticeExtra_0.6-28
 [7] RColorBrewer_1.1-2 effects_4.0-3      lattice_0.20-38
[10] truncdist_1.0-2    evd_2.3-3          sure_0.2.0
[13] sandwich_2.5-0     lmtest_0.9-36      zoo_1.8-4
[16] mgcv_1.8-28        nlme_3.1-137       car_3.0-2
[19] carData_3.0-1      MASS_7.3-51.1      sp_1.3-1

loaded via a namespace (and not attached):
 [1] Rcpp_1.0.0        assertthat_0.2.0  R6_2.3.0
 [4] cellranger_1.1.0  survey_3.33-2     pillar_1.3.0
 [7] rlang_0.3.0.1     lazyeval_0.2.1    curl_3.2
[10] readxl_1.1.0      minqa_1.2.4       data.table_1.11.4
[13] nloptr_1.0.4      Matrix_1.2-17     labeling_0.3
[16] splines_3.5.3     rgdal_1.3-6       lme4_1.1-18-1
[19] foreign_0.8-71    munsell_0.5.0     compiler_3.5.3
[22] pkgconfig_2.0.2   nnet_7.3-12       tidyselect_0.2.5
[25] tibble_1.4.2      rio_0.5.10        crayon_1.3.4
[28] dplyr_0.7.8       withr_2.1.2       grid_3.5.3
[31] gtable_0.2.0      magrittr_1.5      scales_1.0.0
[34] zip_1.0.0         bindrcpp_0.2.2    openxlsx_4.1.0
```

```
[37] tools_3.5.3       forcats_0.3.0     glue_1.3.0
[40] purrr_0.2.5       hms_0.4.2         abind_1.4-5
[43] survival_2.43-3   colorspace_1.3-2  bindr_0.1.1
[46] haven_1.1.2
```

A Custom functions

A.1 Surrogate Residuals

The R package `sure` allows to simulate the surrogate residuals from a large panel of ordered parametric models (https://koalaverse.github.io/sure/index.html) but not for the semiparametric ordered generalized additive model fitted with the package `mgcv`. We first define the `truncLogis` function for the simulation of random draws from a truncated logistic distribution with a vector of inputs (locations and thresholds) as the package `truncdist` is only designed for a given value of location and thresholds. Then, we code the function `surePOLR` which simulate surrogate residuals from `polr` models from the `MASS` package. The code is test against the surrogate simulations from `sure` for a random ordered logistic model.

```
truncLogis <- function(n, spec, a = -Inf, b = Inf, ...) {
    p <- runif(n, min = 0, max = 1)
    G <- get(paste("p", spec, sep = ""), mode = "function")
    Gin <- get(paste("q", spec, sep = ""), mode = "function")
    G.a <- G(a, ...)
    G.b <- G(b, ...)
    pmin(pmax(a, Gin(G(a, ...) + p * (G(b, ...) - G(a, ...)), ...)), b)
}

surePOLR <- function(mod, newd= NULL){
    if (mod$method!= "logistic") stop("Logistic required")
    gg <- as.numeric(mod$zeta)
    if (is.null(newd)){
        g1 <- as.integer(model.response(model.frame(mod)))
        g6 <- mod$lp
    } else {
        g1 <- as.integer(newd[, "AOCc"])
        g6 <- gg[ 1]-qlogis(predict(mod, newdata= newd, type= 'probs')[, 1])
    }
    nn <- length(g1)
    suls <- sapply(g1, switch,
                   "1"= c(-Inf  , gg[ 1]), "2"= c(gg[ 1], gg[ 2]),
                   "3"= c(gg[ 2], gg[ 3]), "4"= c(gg[ 3], gg[ 4]),
                   "5"= c(gg[ 4], Inf   ))
    sls <- data.frame(unlist(t(suls)))
    truncLogis(nn, spec= "logis", a= sls[, 1], b= sls[, 2],
               location= g6, scale= 1)
}
library(MASS) ; library(sure) ; library(truncdist)
fit.polr <- polr(factor(AOCc)~ poly(DEM, 2)+ poly(SLOPE, 2)
                + poly(RAYAT, 2)+ poly(ASPECT, 2)+ poly(PERMEA, 2)
              , data= Reg.Rank)
sure1 <- surrogate(fit.polr)+ fit.polr$zeta[ 1]
sure2 <- resids(fit.polr)
polr1 <- surePOLR(fit.polr) ; polr2 <- surePOLR(fit.polr)- fit.polr$lp
```

Now we use the same structure to simulate the surrogate residuals for the OGAM through the function `sureOGAM`. Again, the function is tested for a random OGAM.

```
sureOGAM <- function(mod, newd= NULL){
    if (is.null(newd)){
        g1 <- as.integer(mod$y)
        g6 <- mod$linear.predictors
    } else {
        g1 <- as.integer(newd[, names(mod$model[ 1])])
        g6 <- predict(mod, newdata= newd)
    }
    nn <- length(g1)
    gt <- data.frame(rep(NA, nn), rep(NA, nn))
    gg <- c(mod$family$getTheta(TRUE), Inf)
    kk <- c(- Inf, gg[ 1])
    for (j in 2: length(unique(g1))) kk <- rbind(kk, c(gg[ j- 1], gg[ j]))
    gt <- data.frame(t(sapply(g1, function(x) kk[x, ])))
    truncLogis(nn, spec= "logis", a= gt[, 1], b= gt[, 2], location= g6)
}
library(mgcv)
fit.ogam <- gam(AOCc~ poly(DEM, 2)+ poly(SLOPE, 2)
                 + poly(RAYAT, 2)+ poly(ASPECT, 2)+ poly(PERMEA, 2)
               , family= ocat(R= 5), data= Reg.Rank)
ogam1 <- sureOGAM(fit.ogam)
ogam2 <- sureOGAM(fit.ogam)- fit.ogam$linear.pred

par(mfrow= c(3, 2))
plot(sure1, polr1)
abline(h= fit.polr$zeta, v= fit.polr$zeta, lty= 2, col= "blue")
abline(0, 1, col= "orange")
plot(sure2, polr2)
abline(0, 1, col= "orange")

plot(polr1, ogam1- mean(ogam1))
abline(h= fit.ogam$family$getTheta(TRUE)- mean(ogam1),
       v= fit.polr$zeta, lty= 2, col= "blue")
abline(0, 1, col= "orange")
plot(polr2, ogam2)
abline(0, 1, col= "orange")

plot(sure1, ogam1- mean(ogam1))
abline(h= fit.ogam$family$getTheta(TRUE)- mean(ogam1),
       v= fit.polr$zeta, lty= 2, col= "blue")
abline(0, 1, col= "orange")
plot(sure2, ogam2)
abline(0, 1, col= "orange")
```

A.2 Decomposition terms

For each terms of the decomposition presented in the main text, we code a different functions presented below. For the ease of notations, we note for the values of the latent and the probabilities of being in each GIs $x = y, p$:

$$\overline{x}_{jc} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \text{and} \quad \overline{x}_{j.} = \frac{1}{C}\sum_{c=1}^{C} x_{jc} \quad \text{and} \quad \overline{x}_{.c} = \frac{1}{J}\sum_{j=1}^{J} x_{jc} \tag{1}$$

The **joint signal** terms is the variance of the expected quality conditionally on vertical and horizontal dummies:

$$\mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y, c]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*) \mid y = j, c = h) - \overline{q}_{jh}]^2 \tag{2}$$

```
jointSignal <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    jS <- rep(0, nrow(dat))
    for (i in unique(dat[, vt])){
        for (j in unique(dat[, hz])){
            tmp <- dat[, vt]== i & dat[, hz]== j
            jS[ tmp] <- mean(dat[tmp, lt])
        }
    }
    c("Joint Signal"= var(jS))
}
```

The **joint noise** terms is the expectation of the variance quality conditionally on vertical and horizontal dummies:

$$\mathbb{E}\{\,\mathbb{V}[q(X^*) \mid y, c]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*) \mid y = j, c = h) - \overline{q}_{jh}]^2 \tag{3}$$

```
jointNoise <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    jN <- 0
    for (i in unique(dat[, vt])){
        for (j in unique(dat[, hz])){
            tmp <- dat[, vt]== i & dat[, hz]== j
            if (sum(tmp)> 1) jN <- jN+ var(dat[ tmp, lt])* mean(tmp)
        }
    }
    c("Joint Noise"= jN)
}
```

The **vertical signal** terms is the variance of the expectation quality conditionally on vertical GI dummies:

$$\mathbb{V}\{\,\mathbb{E}[q(X^*) \mid y]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*) \mid y = j, c = h) - \overline{q}_{jh}]^2 \tag{4}$$

```
vertiSignal <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    vS <- rep(0, nrow(dat))
    for (i in unique(dat[, vt])){
        vS[ dat[, vt]== i] <- mean(dat[dat[, vt]== i, lt])
    }
    c("Vertical Signal"= var(vS))
}
```

The **vertical residual** terms is the expectation of the conditional on horizontal variance of the expectation quality conditionally on vertical GI dummies:

$$\mathbb{E}\{\,\mathbb{V}[\mathbb{E}(q(X^*)\mid y,c)\mid y]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*)\mid y=j,c=h)-\overline{q}_{jh}]^2 \tag{5}$$

```
vertiResid <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    sig <- rep(0, nrow(dat)) ; vR <- 0
    for (i in unique(dat[, vt])){
        for (j in unique(dat[, hz])){
            tmp <- dat[, vt]== i & dat[, hz]== j
            sig[ tmp] <- mean(dat[ tmp, lt])
        }
    }
    for (i in unique(dat[, vt])){
        vR <- vR+ var(sig[dat[, vt]== i])* mean(dat[, vt]== i)
    }
    c("Vertical Residual"= vR)
}
```

The **vertical Noise** terms is the expectation of the variance of the quality conditionally on vertical GI dummies:

$$\mathbb{E}\{\,\mathbb{V}[q(X^*)\mid y]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*)\mid y=j,c=h)-\overline{q}_{jh}]^2 \tag{6}$$

```
vertiNoise <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    vN <- 0
    for (i in unique(dat[, vt])){
        vN <- vN+ var(dat[dat[, vt]== i, lt])* mean(dat[, vt]== i)
    }
    c("Vertical Noise"= vN)
}
```

The **horizontal signal** terms is the variance of the expectation quality conditionally on horizontal GI dummies:

$$\mathbb{V}\{\,\mathbb{E}[q(X^*)\mid c]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*)\mid y=j, c=h) - \overline{q}_{jh}]^2 \tag{7}$$

```
horizSignal <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    hS <- rep(0, nrow(dat))
    for (j in unique(dat[, hz])){
        hS[ dat[, hz]== j] <- mean(dat[dat[, hz]== j, lt])
    }
    c("Horizontal Signal"= var(hS))
}
```

The **horizontal residual** terms is the expectation of the conditional on vertical variance of the expectation quality conditionally on horizontal GI dummies:

$$\mathbb{E}\{\,\mathbb{V}[\mathbb{E}(q(X^*)\mid y, c)\mid y]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*)\mid y=j, c=h) - \overline{q}_{jh}]^2 \tag{8}$$

```
horizResid <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    sig <- rep(0, nrow(dat)) ; hR <- 0
    for (i in unique(dat[, vt])){
        for (j in unique(dat[, hz])){
            tmp <- dat[, vt]== i & dat[, hz]== j
            sig[ tmp] <- mean(dat[ tmp, lt])
        }
    }
    for (j in unique(dat[, hz])){
        hR <- hR+ var(sig[dat[, hz]== j])* mean(dat[, hz]== j)
    }
    c("Horizontal Residual"= hR)
}
```

The **horizontal Noise** terms is the expectation of the variance of the quality conditionally on horizontal GI dummies:

$$\mathbb{E}\{\,\mathbb{V}[q(X^*)\mid c]\,\} = \frac{1}{N+J+H}\sum_{i=1}^{N}\sum_{j=1}^{J}\sum_{h=1}^{H}[\mathbb{E}(q(X^*)\mid y=j, c=h) - \overline{q}_{jh}]^2 \tag{9}$$

```
horizNoise <- function(dat, lt, vt= "AOCc", hz= "LIBCOM"){
    hN <- 0
    for (j in unique(dat[, hz])){
        hN <- hN+ (var(dat[dat[, hz]== j, lt])* mean(dat[, hz]== j))
    }
    c("Horizontal Noise"= hN)
```

```
}
```