

# Longitudinal Data Analysis Exam

*Joschka Hüllmann*

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## Introduction

Conventional wisdom suggests that the influence of the Supreme Court justices' ideology becomes more politically moderate over time. I test this hypothesis using a data set on the voting patterns of justices sitting on the Supreme Court during the Vinson, Warren, Burger, Rehnquist, and Roberts courts (1946-2017) with  $N = 38, T = 72$ , *unbalanced*. In particular, I analyse the effect of the normed "Segal/Cover" (SC) score of the justice (time invariant) and the "Martin/Quinn" (MQ) score of the justice (time variant) on the percentage of liberal (left) votes casted by the justice. If the hypothesis holds, then SC should have a positive effect on the votes, while the interaction between SC and time should have a negative effect. Since MQ uses an inversed scale compared to SC, the results for MQ should be the opposite.

## Analysis

Listing 1 shows the loading and pre-processing of the data.

```
library(RCurl)
library(dplyr)
library(geepack)
library(glmmML)
library(ggplot2)
library(plm)
library(lme4)
library(lmtest)
library(zoo)
library(survival)
setwd("C:\\dev\\workspace\\GSERM-Oslo-2019-git\\Final Exam-Solution")
df<-read.csv("../Final Exam\\GSERM-Oslo-2019-Exam-Q1-Data.csv")
df<-df[,c(2,3,6,8,9)]
df<-df %>% arrange(JusticeName, Term) %>% group_by(JusticeName) %>% mutate(rank(Term, ties.method="first")
names(df)[6]<-"Year"
df$Economics<-df$Economics/100
df<-filter(df, is.na(Economics)==FALSE, is.na(SCIdeology)==FALSE,
           is.na(MQScore)==FALSE, is.na(Term)==FALSE,
           is.na(Year)==FALSE) %>% as.data.frame()
```

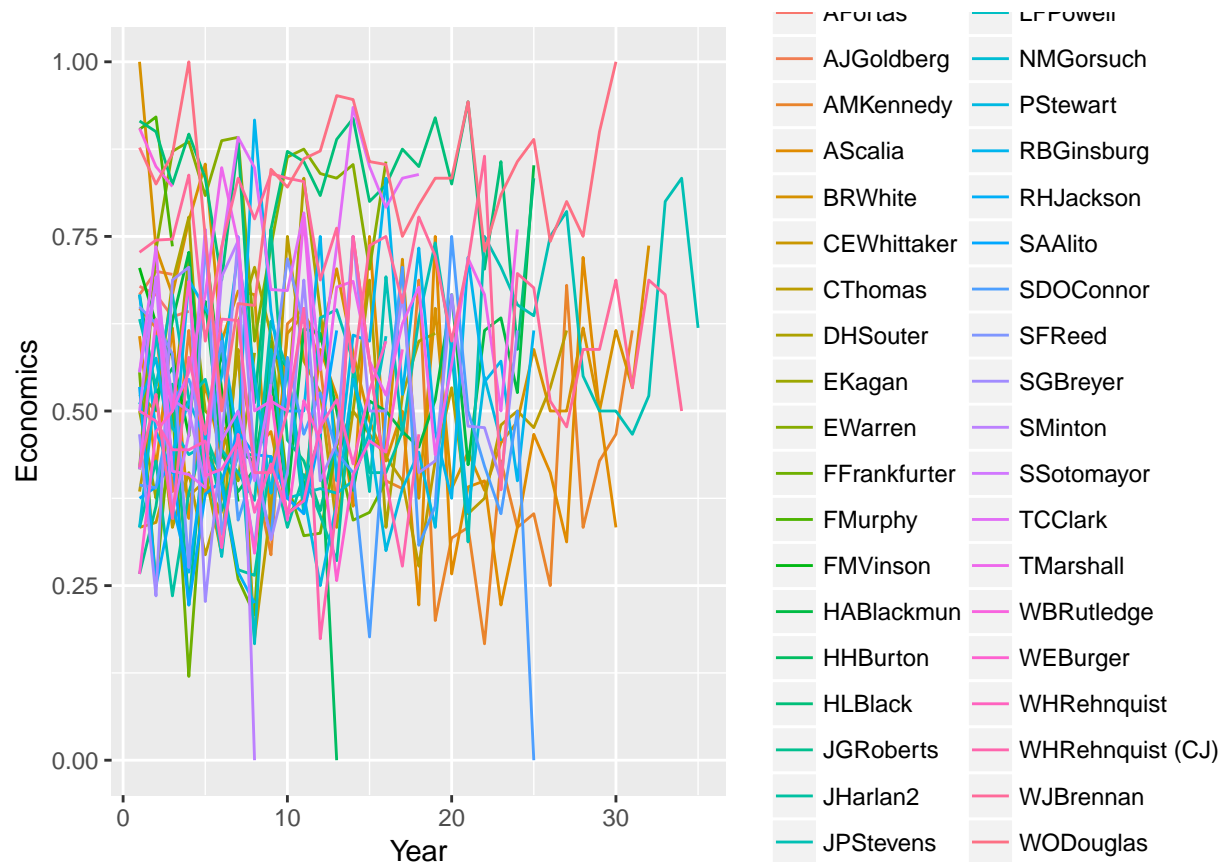
Listing 2 shows the descriptive statistics of the data. On a first glance, I can see no patterns that would support the hypothesis.

```
summary(df)
```

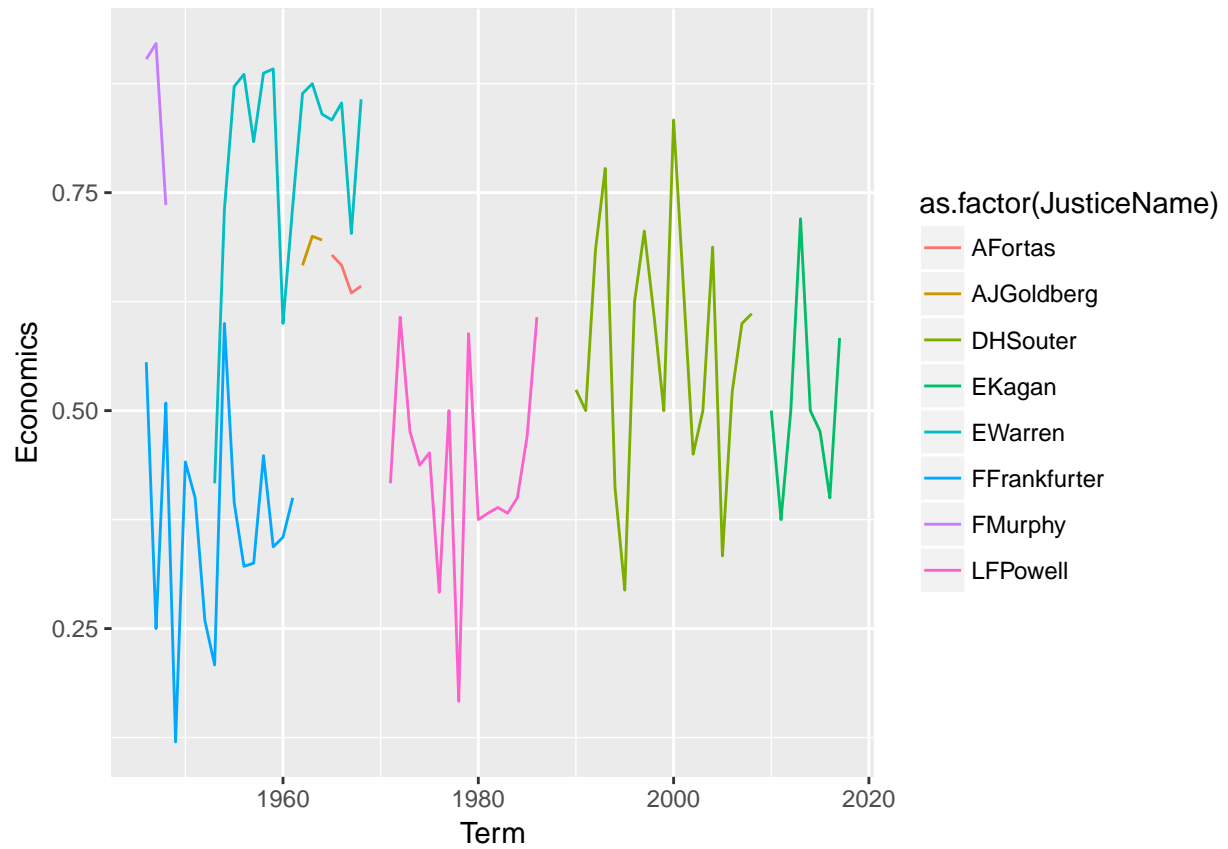
##	JusticeName	Term	Economics	SCIdeology
##	JPStevens: 35	Min. :1946	Min. :0.0000	Min. :0.0000
##	WJBrennan: 34	1st Qu.:1963	1st Qu.:0.4118	1st Qu.:0.1650
##	BRWhite : 32	Median :1981	Median :0.5161	Median :0.5000
##	AMKennedy: 31	Mean :1981	Mean :0.5480	Mean :0.4925
##	AScalia : 30	3rd Qu.:1999	3rd Qu.:0.6857	3rd Qu.:0.7500
##	WODouglas: 30	Max. :2017	Max. :1.0000	Max. :1.0000

```
## (Other) :461
##      MQScore      Year
## Min.   :-7.74800   Min.    : 1.00
## 1st Qu.: -1.42700   1st Qu.: 5.00
## Median : 0.37500   Median :10.00
## Mean   :-0.02485   Mean    :11.77
## 3rd Qu.: 1.35000   3rd Qu.:17.00
## Max.    : 4.51100   Max.     :35.00
##
```

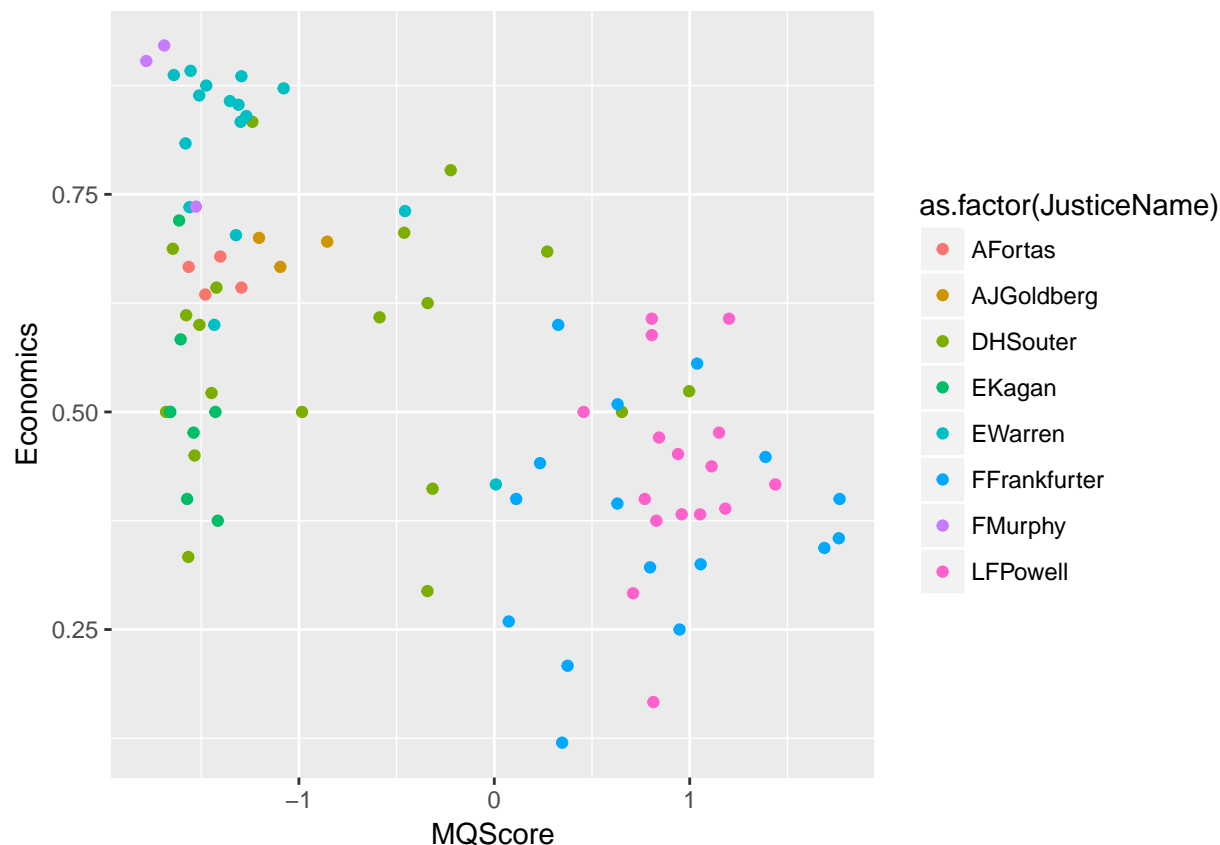
```
ggplot(df, aes(Year, Economics)) + geom_line(aes(colour=as.factor(JusticeName)))
```



```
ggplot(df[which(df$JusticeName %in% c("AFortas", "AJGoldberg", "LFPowell", "DHSouter", "EKagan", "FMurphy", "FMVinson", "HABlackmun", "HHBurton", "HLBlack", "JGRoberts", "JHarlan2", "JPStevens", "LFPowell", "NMGorsuch", "PStewart", "RBGinsburg", "RHJackson", "SAAlito", "SDOConnor", "SFReed", "SGBreyer", "SMinton", "SSotomayor", "TCClark", "TMarshall", "WBRutledge", "WEBurger", "WHRehnquist", "WHRehnquist (CJ)", "WJBrennan", "WODouglas"))])
```



```
ggplot(df[which(df$JusticeName %in% c("AFortas", "AJGoldberg", "LFPowell", "DHSouter", "EKagan", "FMurphy", "FFrankfurter", "EWarren"))])
```



Listing 3 shows basic OLS models. Ideology is positively associated with the votes as expected, supporting the hypothesis.

```
fit.ols<-lm(Economics~SCIdeology+MQScore+Year, df)
fit.ols.ie<-lm(Economics~SCIdeology+MQScore+SCIdeology*Year, df)
fit.ols.ie2<-lm(Economics~SCIdeology+MQScore+SCIdeology*Year+MQScore*Year, df)
summary(fit.ols)
```

```
##
## Call:
## lm(formula = Economics ~ SCIdeology + MQScore + Year, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.53146 -0.11257 -0.00513  0.11218  0.42014
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.5459579  0.0181010  30.162  <2e-16 ***
## SCIdeology   0.0491118  0.0238592   2.058   0.0400 *
## MQScore     -0.0405618  0.0036666 -11.063  <2e-16 ***
## Year        -0.0019678  0.0008246  -2.386   0.0173 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1558 on 649 degrees of freedom
## Multiple R-squared:  0.2733, Adjusted R-squared:  0.2699
```

```
## F-statistic: 81.35 on 3 and 649 DF, p-value: < 2.2e-16
```

```
summary(fit.ols.ie)
```

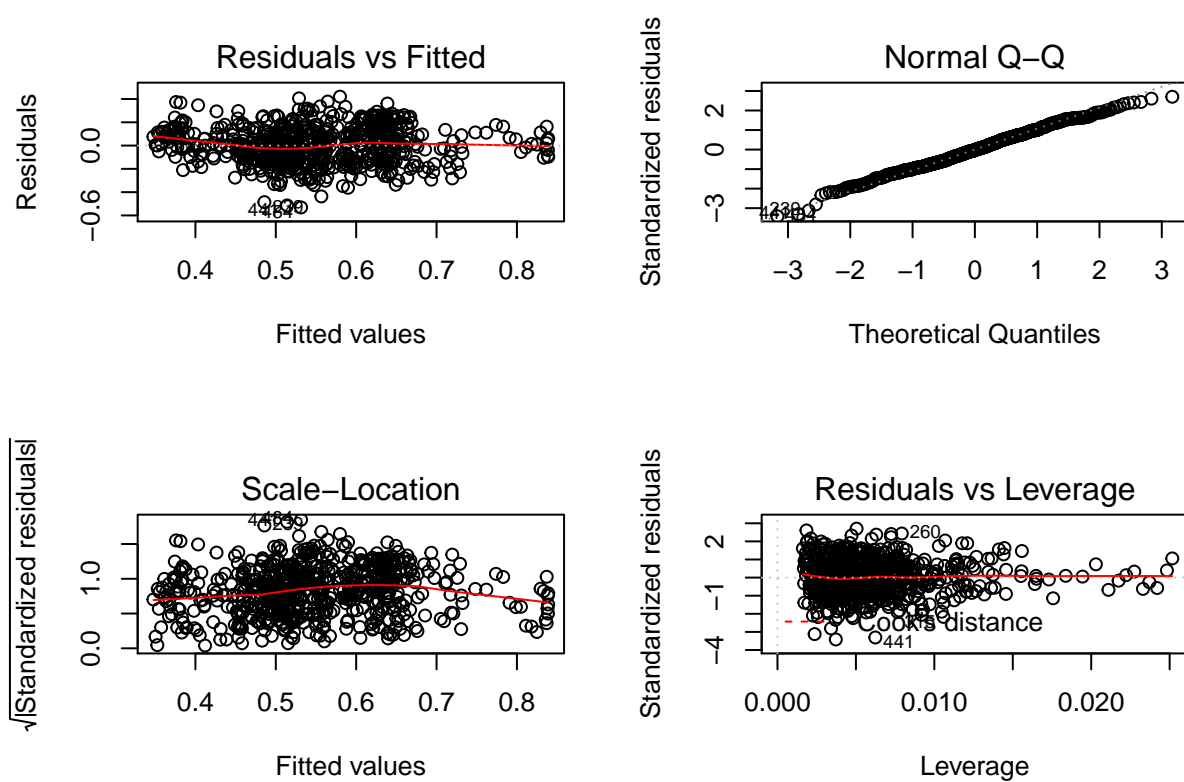
```
##
## Call:
## lm(formula = Economics ~ SCIdeology + MQScore + SCIdeology *
##     Year, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.53259 -0.11250 -0.00331  0.11134  0.42015
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.5324768  0.0223540   23.820  <2e-16 ***
## SCIdeology      0.0758711  0.0353159    2.148   0.0321 *
## MQScore        -0.0409376  0.0036846  -11.110  <2e-16 ***
## Year           -0.0007725  0.0014257   -0.542   0.5881
## SCIdeology:Year -0.0024136  0.0023485   -1.028   0.3045
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1558 on 648 degrees of freedom
## Multiple R-squared:  0.2745, Adjusted R-squared:  0.27
## F-statistic: 61.28 on 4 and 648 DF, p-value: < 2.2e-16
```

```
summary(fit.ols.ie2)
```

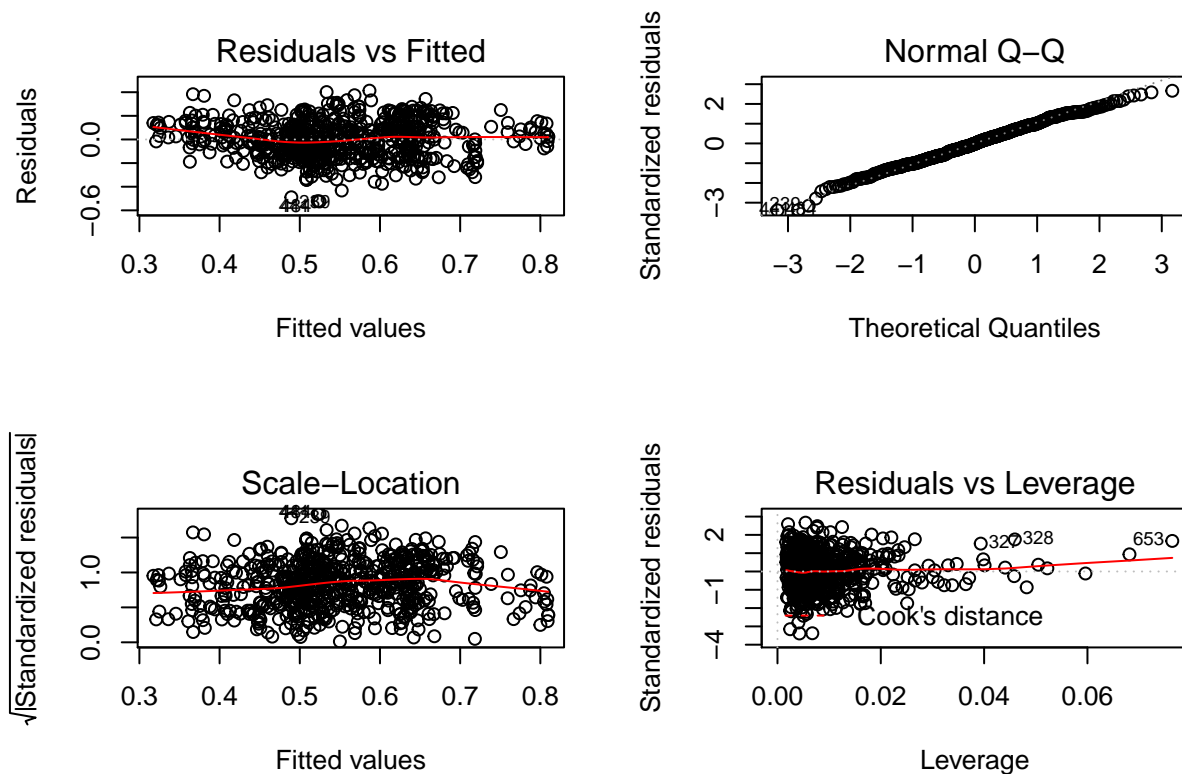
```
##
## Call:
## lm(formula = Economics ~ SCIdeology + MQScore + SCIdeology *
##     Year + MQScore * Year, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.52475 -0.11007 -0.00116  0.11150  0.41310
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.5614699  0.0256458   21.893  < 2e-16 ***
## SCIdeology      0.0233361  0.0420538    0.555   0.5791
## MQScore        -0.0565795  0.0077729  -7.279 9.78e-13 ***
## Year           -0.0022707  0.0015653   -1.451   0.1474
## SCIdeology:Year  0.0010166  0.0027815    0.365   0.7149
## MQScore:Year     0.0009478  0.0004151    2.283   0.0227 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1553 on 647 degrees of freedom
## Multiple R-squared:  0.2803, Adjusted R-squared:  0.2747
## F-statistic: 50.39 on 5 and 647 DF, p-value: < 2.2e-16
```

```
par(mfrow=c(2,2))
```

```
plot(fit.ols)
```



```
plot(fit.ols.ie2)
```



Listing 4 shows fixed and random effects models. Fixed effect does not make any sense, because our covariate of main interest, i.e. SCIdeology, is time invariant and therefore is excluded from model. The Hausman test suggests likewise. For the random effects model ( $Y_{it} = f(X_{it}\beta + \alpha_i + u_{it})$ ,  $f$  is logit link for `glmm` and `glmer` and identify link for `plm` package) the random effect must be independent of the other independent variables ( $cov(x_{it}, \alpha_i) = 0$ , with  $x_{it}$  being the covariates and  $\alpha_i$  being the random effects). Substantively, it is a little bit difficult to justify this, because the political ideology of a justice is influenced by many individual-specific effects, e.g. where they grew up, the ideology of their parents and social circle, past experience, professional history, etc. Another assumption to discuss is within-unit correlation. So far we have assumed no correlation within units. The plots show that for the linear random effects panel model, the residuals are uncorrelated and look fine. However, for the generalised models, there seems to be a systematic correlation. Substantively, this is related to the conventional wisdom that justices become more moderate over time. Analytically, the durbin watson test can be used to check this. In our case it confirms our assumptions about the models. To deal with this dynamic, we already included the time parameter in the model in a linear, non-unit specific way. For auto correlation, we can also fit the models with a correlation structure. Unfortunately, the packages for generalised linear models that we use here do not support this (though, it seems that the function `glmmPQL` from the MASS package can do this). Since we are not explicitly interested in unit level effect, but rather acknowledge their existence, we can choose a straight-forward way out and use a generalised estimating equation (GEE) model, i.e. a population average model.

Note: I am not sure why `glmmML` and `glmer` show such different results. They should both be fitted with the Gauss-Hermite Quadrature with equivalent model specifications. No hausman test is available for the packages. Some guy on StackOverflow ported it apparently (<https://stackoverflow.com/a/23635004>).

```
# fixed effects
fit.glmm.fe <- glmmboot(Economics~SCIdeology+MQScore+Year, data=df, family="binomial", cluster=JusticeN

## Warning in glmmbootFit(X, Y, weights, start.coef, cluster, offset,
```

```
## family, : non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!
summary(fit.glmm.fe)

##
## Call: glmmboot(formula = Economics ~ SCIdeology + MQScore + Year, family = "binomial", data = c
##
##
##              coef se(coef)      z Pr(>|z|)
## SCIdeology -8.951e-09 8.610e+06 -1.040e-15  1.000
## MQScore    -1.234e-01 1.304e-01 -9.462e-01  0.344
## Year       -1.213e-02 1.443e-02 -8.411e-01  0.400
##
## Residual deviance: 47.19 on 612 degrees of freedom  AIC: 129.2
fit.glmm.fe.i <- glmmboot(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year, data=df, fami

## Warning in glmmbootFit(X, Y, weights, start.coef, cluster, offset,
## family, : non-integer #successes in a binomial glm!

## Warning in glmmbootFit(X, Y, weights, start.coef, cluster, offset,
## family, : non-integer #successes in a binomial glm!

## info[dpoco] = 1

## Warning in glmmbootFit(X, Y, weights, start.coef, cluster, offset,
## family, : [glmmboot:] Information non-positive definite. No variance!
summary(fit.glmm.fe.i)

##
## Call: glmmboot(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology * Year + MQScore
##
##
##              coef se(coef)      z Pr(>|z|)
## SCIdeology    -2.705e-09      NA NA      NA
## MQScore       -1.550e-01      NA NA      NA
## Year          -2.978e-03      NA NA      NA
## SCIdeology:Year -2.205e-02      NA NA      NA
## MQScore:Year    7.903e-04      NA NA      NA
##
## Residual deviance: 46.75 on 610 degrees of freedom  AIC: 132.8
# random effects
fit.glmm.re <- glmmML(Economics~SCIdeology+MQScore+Year, data=df, family="binomial", cluster=JusticeNam

## Warning in glmmML.fit(X, Y, weights, cluster.weights, start.coef,
## start.sigma, : non-integer #successes in a binomial glm!

## Warning in glmmML.fit(X, Y, weights, cluster.weights, start.coef,
## start.sigma, : non-integer #successes in a binomial glm!
summary(fit.glmm.re)

##
## Call: glmmML(formula = Economics ~ SCIdeology + MQScore + Year, family = "binomial", data = df
```



```
##
##
##           coef se(coef)          z Pr(>|z|)
## (Intercept)  0.202337  0.23734  0.8525 0.394000
## SCIdeology   0.182171  0.31348  0.5811 0.561000
## MQScore      -0.175192  0.05059 -3.4629 0.000534
## Year         -0.008007  0.01081 -0.7407 0.459000
##
## Scale parameter in mixing distribution: 5.191e-07 gaussian
## Std. Error:                                0.1336
##
## LR p-value for H_0: sigma = 0: 0.5
##
## Residual deviance: 71.13 on 648 degrees of freedom AIC: 81.13
fit.glmm.re.i <- glmmML(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year, data=df, family=
## Warning in glmmML.fit(X, Y, weights, cluster.weights, start.coef,
## start.sigma, : non-integer #successes in a binomial glm!

## Warning in glmmML.fit(X, Y, weights, cluster.weights, start.coef,
## start.sigma, : non-integer #successes in a binomial glm!
summary(fit.glmm.re.i)

##
## Call: glmmML(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology *          Year + MQScore *
##
##
##           coef se(coef)          z Pr(>|z|)
## (Intercept)   0.264091 0.336324  0.7852  0.4320
## SCIdeology     0.083794 0.550687  0.1522  0.8790
## MQScore        -0.236577 0.104673 -2.2602  0.0238
## Year           -0.009567 0.020535 -0.4659  0.6410
## SCIdeology:Year 0.004254 0.036693  0.1159  0.9080
## MQScore:Year   0.003735 0.005645  0.6617  0.5080
##
## Scale parameter in mixing distribution: 1.514e-06 gaussian
## Std. Error:                                0.1322
##
## LR p-value for H_0: sigma = 0: 0.5
##
## Residual deviance: 70.62 on 646 degrees of freedom AIC: 84.62
# random effects with glmer
fit.glmer.re2 <- glmer(Economics~SCIdeology+MQScore+Year + (1|JusticeName), data=df, family="binomial")

## Warning in eval(family$initialize, rho): non-integer #successes in a
## binomial glm!
summary(fit.glmer.re2)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: Economics ~ SCIdeology + MQScore + Year + (1 | JusticeName)
## Data: df
```

```
##
##      AIC      BIC    logLik deviance df.resid
##    793.1    815.5   -391.6    783.1     648
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.33605 -0.22422  0.07787  0.34317  1.67236
##
## Random effects:
##  Groups      Name      Variance Std.Dev.
##  JusticeName (Intercept) 1.101e-10 1.049e-05
## Number of obs: 653, groups:  JusticeName, 38
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.03176    0.25327   0.125   0.9002
## SCIdeology   0.55629    0.33250   1.673   0.0943 .
## MQScore     -0.42965    0.06119  -7.021  2.2e-12 ***
## Year        -0.01795    0.01167  -1.538   0.1241
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) SCIdlg MQScor
## SCIdeology  -0.788
## MQScore     -0.562  0.535
## Year        -0.692  0.248  0.355

fit.glmer.re2.i <- glmer(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year + (1|JusticeName)

## Warning in eval(family$initialize, rho): non-integer #successes in a
## binomial glm!

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control
## $checkConv, : Model failed to converge with max|grad| = 0.00103181 (tol =
## 0.001, component 1)

summary(fit.glmer.re2.i)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: Economics ~ SCIdeology + MQScore + Year + SCIdeology * Year +
##      MQScore * Year + (1 | JusticeName)
## Data: df
##
##      AIC      BIC    logLik deviance df.resid
##    796.9    828.3   -391.5    782.9     646
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.33755 -0.22530  0.07767  0.33748  1.66572
##
## Random effects:
##  Groups      Name      Variance Std.Dev.
##  JusticeName (Intercept) 2.498e-10 1.58e-05
```

```

## Number of obs: 653, groups:  JusticeName, 38
##
## Fixed effects:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.110333   0.354807   0.311   0.756
## SCIdeology     0.415584   0.576517   0.721   0.471
## MQScore       -0.469948   0.118879  -3.953 7.71e-05 ***
## Year          -0.022682   0.022202  -1.022   0.307
## SCIdeology:Year 0.010322   0.039589   0.261   0.794
## MQScore:Year   0.002678   0.006715   0.399   0.690
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) SCIdlg MQScor Year   SCId:Y
## SCIdeology  -0.895
## MQScore     -0.577  0.553
## Year        -0.840  0.762  0.404
## SCIdelgy:Yr  0.687 -0.810 -0.386 -0.851
## MQScore:Yer  0.439 -0.469 -0.859 -0.366  0.460
## convergence code: 0
## Model failed to converge with max|grad| = 0.00103181 (tol = 0.001, component 1)
# conditional fixed effects with coxph
fit.clogit <- clogit(Economics~SCIdeology+MQScore+Year+strata(JusticeName), data=df)

## Warning in Surv(rep(1, 653L), Economics): Invalid status value, converted
## to NA

## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, :
## Ran out of iterations and did not converge

summary(fit.clogit)

## Call:
## coxph(formula = Surv(rep(1, 653L), Economics) ~ SCIdeology +
##       MQScore + Year + strata(JusticeName), data = df, method = "exact")
##
## n= 6, number of events= 3
## (647 observations deleted due to missingness)
##
##           coef exp(coef) se(coef)  z Pr(>|z|)
## SCIdeology    0         1         0 NA      NA
## MQScore        0         1         0 NA      NA
## Year           0         1         0 NA      NA
##
##           exp(coef) exp(-coef) lower .95 upper .95
## SCIdeology         1         1         1         1
## MQScore            1         1         1         1
## Year               1         1         1         1
##
## Concordance= NaN (se = NaN )
## Rsquare= 0 (max possible= 0 )
## Likelihood ratio test= 0 on 3 df,  p=1
## Wald test              = 0 on 3 df,  p=1
## Score (logrank) test = 0 on 3 df,  p=1

```

```

fit.clogit.i <- clogit(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year+strata(JusticeName))

## Warning in Surv(rep(1, 653L), Economics): Invalid status value, converted
## to NA

## Warning in Surv(rep(1, 653L), Economics): Ran out of iterations and did not
## converge

summary(fit.clogit.i)

## Call:
## coxph(formula = Surv(rep(1, 653L), Economics) ~ SCIdeology +
##       MQScore + Year + SCIdeology * Year + MQScore * Year + strata(JusticeName),
##       data = df, method = "exact")
##
##      n= 6, number of events= 3
##      (647 observations deleted due to missingness)
##
##              coef exp(coef) se(coef)      z Pr(>|z|)
## SCIdeology      0         1         0 NA      NA
## MQScore         0         1         0 NA      NA
## Year            0         1         0 NA      NA
## SCIdeology:Year  0         1 8613223   0      1
## MQScore:Year    0         1         0 NA      NA
##
##              exp(coef) exp(-coef) lower .95 upper .95
## SCIdeology          1         1         1         1
## MQScore             1         1         1         1
## Year                1         1         1         1
## SCIdeology:Year     1         1         0      Inf
## MQScore:Year        1         1         1         1
##
## Concordance= NaN (se = NaN )
## Rsquare= 0 (max possible= 0 )
## Likelihood ratio test= 0 on 5 df,  p=1
## Wald test              = 0 on 5 df,  p=1
## Score (logrank) test = 0 on 5 df,  p=1

# fixed effect lsdv with glm
fit.lsdv <- glm(Economics~SCIdeology+MQScore+Year+as.factor(JusticeName), data=df,family=binomial)

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

fit.lsdv.i <- glm(Economics~SCIdeology+MQScore+SCIdeology*Year+MQScore*Year+as.factor(JusticeName), data=df,family=binomial)

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

# fixed and random effect with plm (without logit as pglm + binomial family does not allow fractions)
fit.plm.fe <- plm(Economics~SCIdeology+MQScore+Year, data=df, index=c("JusticeName"), model="within")
summary(fit.plm.fe)

## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = Economics ~ SCIdeology + MQScore + Year, data = df,

```

```

##      model = "within", index = c("JusticeName"))
##
## Unbalanced Panel: n = 38, T = 2-35, N = 653
##
## Residuals:
##      Min.      1st Qu.      Median      3rd Qu.      Max.
## -0.5088322 -0.0801865  0.0046442  0.0774447  0.3521348
##
## Coefficients:
##              Estimate Std. Error t-value Pr(>|t|)
## MQScore -0.02516490  0.00761290 -3.3056 0.001003 **
## Year    -0.00267920  0.00089438 -2.9956 0.002850 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    10.551
## Residual Sum of Squares: 10.335
## R-Squared:    0.0204
## Adj. R-Squared: -0.041924
## F-statistic: 6.38283 on 2 and 613 DF, p-value: 0.0018049
fit.plm.fe2.i <- plm(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year, data=df, index=c("JusticeName"))
summary(fit.plm.fe2.i)

## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology *
##      Year + MQScore * Year, data = df, model = "within", index = c("JusticeName"))
##
## Unbalanced Panel: n = 38, T = 2-35, N = 653
##
## Residuals:
##      Min.      1st Qu.      Median      3rd Qu.      Max.
## -0.5064240 -0.0806061  0.0047038  0.0737135  0.3451360
##
## Coefficients:
##              Estimate Std. Error t-value Pr(>|t|)
## MQScore      -0.03162489  0.01352861 -2.3376 0.01973 *
## Year          -0.00057192  0.00166724 -0.3430 0.73169
## SCIdeology:Year -0.00473924  0.00288188 -1.6445 0.10059
## MQScore:Year    0.00015745  0.00046613  0.3378 0.73564
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    10.551
## Residual Sum of Squares: 10.246
## R-Squared:    0.028887
## Adj. R-Squared: -0.036278
## F-statistic: 4.54368 on 4 and 611 DF, p-value: 0.0012685
fit.plm.re <- plm(Economics~SCIdeology+MQScore+Year, data=df, index=c("JusticeName"), model="random")
summary(fit.plm.re)

## Oneway (individual) effect Random Effect Model

```

```

## (Swamy-Arora's transformation)
##
## Call:
## plm(formula = Economics ~ SCIdeology + MQScore + Year, data = df,
##      model = "random", index = c("JusticeName"))
##
## Unbalanced Panel: n = 38, T = 2-35, N = 653
##
## Effects:
##              var std.dev share
## idiosyncratic 0.016860 0.129847 0.682
## individual    0.007848 0.088590 0.318
## theta:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.2804 0.6559 0.7134 0.6855 0.7415 0.7595
##
## Residuals:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.52386 -0.08419 0.00651 0.00146 0.09162 0.36293
##
## Coefficients:
##              Estimate Std. Error z-value Pr(>|z|)
## (Intercept) 0.53017430 0.03516776 15.0756 < 2.2e-16 ***
## SCIdeology 0.08414324 0.05352150 1.5721 0.1159183
## MQScore -0.03230350 0.00628865 -5.1368 2.795e-07 ***
## Year -0.00292793 0.00084366 -3.4705 0.0005195 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares: 12.946
## Residual Sum of Squares: 11.07
## R-Squared: 0.14593
## Adj. R-Squared: 0.14198
## Chisq: 109.985 on 3 DF, p-value: < 2.22e-16
fit.plm.re2.i <- plm(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year, data=df, index=c("JusticeName"))
summary(fit.plm.re2.i)

## Oneway (individual) effect Random Effect Model
## (Swamy-Arora's transformation)
##
## Call:
## plm(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology *
##      Year + MQScore * Year, data = df, model = "random", index = c("JusticeName"))
##
## Unbalanced Panel: n = 38, T = 2-35, N = 653
##
## Effects:
##              var std.dev share
## idiosyncratic 0.016769 0.129495 0.669
## individual    0.008311 0.091162 0.331
## theta:
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.2913 0.6654 0.7215 0.6941 0.7490 0.7665
##

```

```
## Residuals:
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -0.52019 -0.08195  0.00504  0.00155  0.09001  0.35681
##
## Coefficients:
##              Estimate Std. Error z-value Pr(>|z|)
## (Intercept)   0.52616983  0.04064914 12.9442 < 2e-16 ***
## SCIdeology    0.09797282  0.06440044  1.5213  0.1282
## MQScore      -0.04316575  0.01079802 -3.9976 6.4e-05 ***
## Year         -0.00118818  0.00156316 -0.7601  0.4472
## SCIdeology:Year -0.00378683  0.00277503 -1.3646  0.1724
## MQScore:Year   0.00044103  0.00042673  1.0335  0.3014
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    12.857
## Residual Sum of Squares: 10.919
## R-Squared:    0.15187
## Adj. R-Squared: 0.14532
## Chisq: 114.894 on 5 DF, p-value: < 2.22e-16
```

```
# overview
overview <- cbind(
  c(0,coef(fit.glmm.fe)),
  coef(fit.lsdv)[1:4],
  c(0,coef(fit.plm.fe),0),
  coef(fit.glmm.re),
  coef(summary(fit.glmer.re2))[1],
  coef(fit.plm.re)
)
colnames(overview) <- c("glmmFE", "lsdv", "plmFE", "glmmRE", "glmerRE", "plmRE")
overview
```

```
##              glmmFE      lsdv      plmFE      glmmRE      glmerRE
##      0.000000e+00  2.76115366  0.000000000  0.202337066  0.03176124
## SCIdeology -8.951041e-09 -2.26330840 -0.025164901  0.182171433  0.55628816
## MQScore   -1.233616e-01 -0.12336163 -0.002679202 -0.175192198 -0.42964509
## Year      -1.213353e-02 -0.01213353  0.000000000 -0.008007015 -0.01794557
##              plmRE
##      0.530174301
## SCIdeology  0.084143245
## MQScore    -0.032303495
## Year       -0.002927933
```

```
overview.i <- cbind(
  coef(fit.glmm.re.i),
  coef(summary(fit.glmer.re2.i))[1],
  coef(fit.plm.re2.i)
)
colnames(overview.i) <- c("glmmRE", "glmerRE", "plmRE")
overview.i
```

```
##              glmmRE      glmerRE      plmRE
## (Intercept)  0.264090506  0.110333068  0.5261698289
## SCIdeology   0.083794205  0.415583771  0.0979728225
## MQScore     -0.236577078 -0.469948301 -0.0431657492
```

```

## Year          -0.009567343 -0.022681586 -0.0011881770
## SCIdeology:Year 0.004253693 0.010321985 -0.0037868304
## MQScore:Year   0.003735173 0.002677836 0.0004410288
# hausman test and breusch-godfrey test
phptest(fit.plm.fe,fit.plm.re)

##
## Hausman Test
##
## data: Economics ~ SCIdeology + MQScore + Year
## chisq = 5.0578, df = 2, p-value = 0.07974
## alternative hypothesis: one model is inconsistent
phptest(fit.plm.fe2.i,fit.plm.re2.i)

##
## Hausman Test
##
## data: Economics ~ SCIdeology + MQScore + Year + SCIdeology * Year + ...
## chisq = 4.5007, df = 4, p-value = 0.3425
## alternative hypothesis: one model is inconsistent
pbgttest(fit.plm.re)

##
## Breusch-Godfrey/Wooldridge test for serial correlation in panel
## models
##
## data: Economics ~ SCIdeology + MQScore + Year
## chisq = 0.78956, df = 2, p-value = 0.6738
## alternative hypothesis: serial correlation in idiosyncratic errors
pbgttest(fit.plm.re2.i)

##
## Breusch-Godfrey/Wooldridge test for serial correlation in panel
## models
##
## data: Economics ~ SCIdeology + MQScore + Year + SCIdeology * Year + MQScore * Year
## chisq = 0.78761, df = 2, p-value = 0.6745
## alternative hypothesis: serial correlation in idiosyncratic errors
# no pbgttest for glmer and glmm...
# durbin watson
pdwtest(fit.plm.re)

##
## Durbin-Watson test for serial correlation in panel models
##
## data: Economics ~ SCIdeology + MQScore + Year
## DW = 1.9529, p-value = 0.2398
## alternative hypothesis: serial correlation in idiosyncratic errors
pdwtest(fit.plm.re)

##

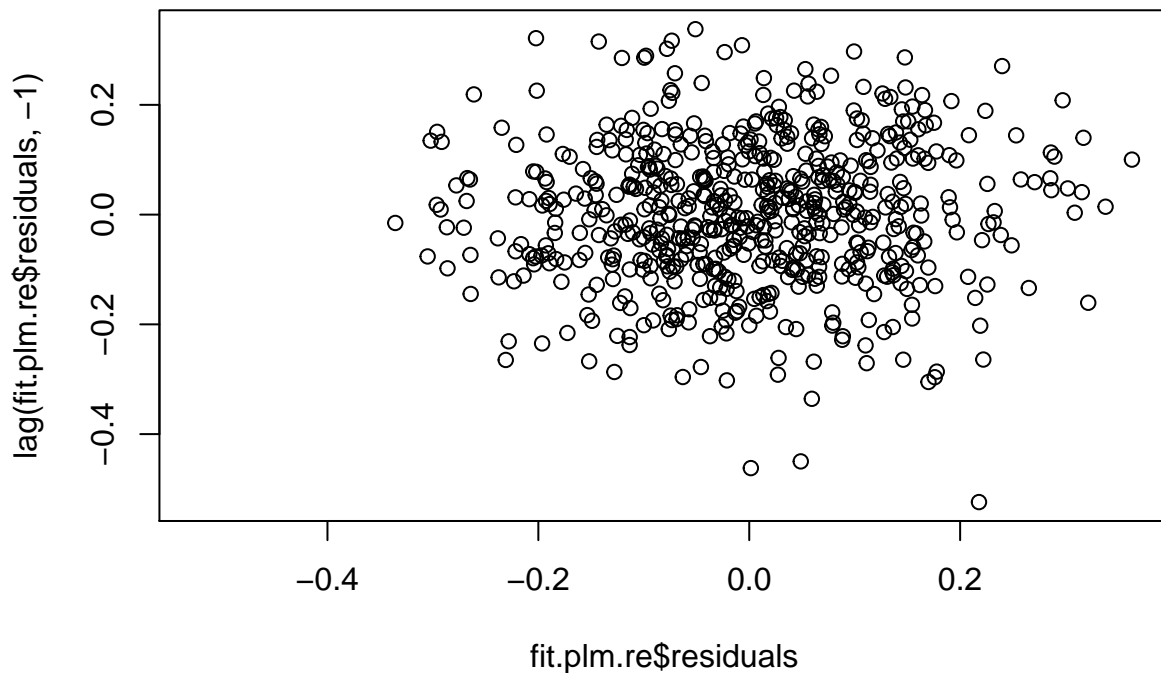
```



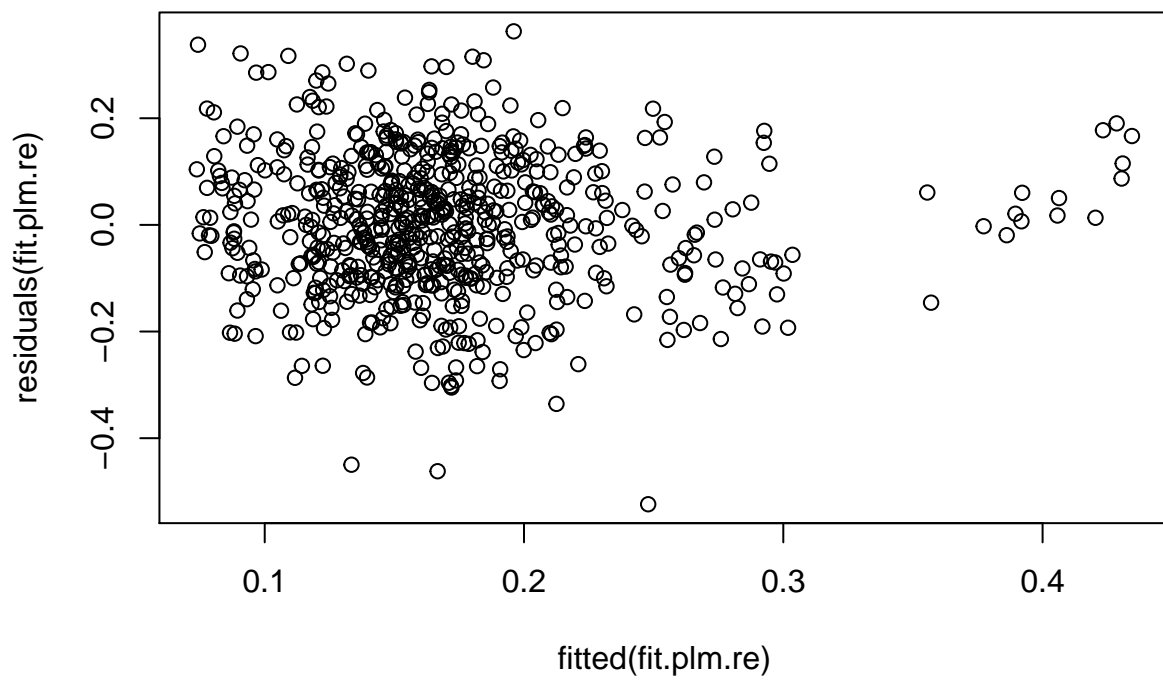
```
## Durbin-Watson test for serial correlation in panel models
##
## data: Economics ~ SCIdeology + MQScore + Year
## DW = 1.9529, p-value = 0.2398
## alternative hypothesis: serial correlation in idiosyncratic errors
pdwtest(fit.plm.re2.i)

##
## Durbin-Watson test for serial correlation in panel models
##
## data: Economics ~ SCIdeology + MQScore + Year + SCIdeology * Year + MQScore * Year
## DW = 1.9641, p-value = 0.2634
## alternative hypothesis: serial correlation in idiosyncratic errors
dwtest(fit.glmm.re)

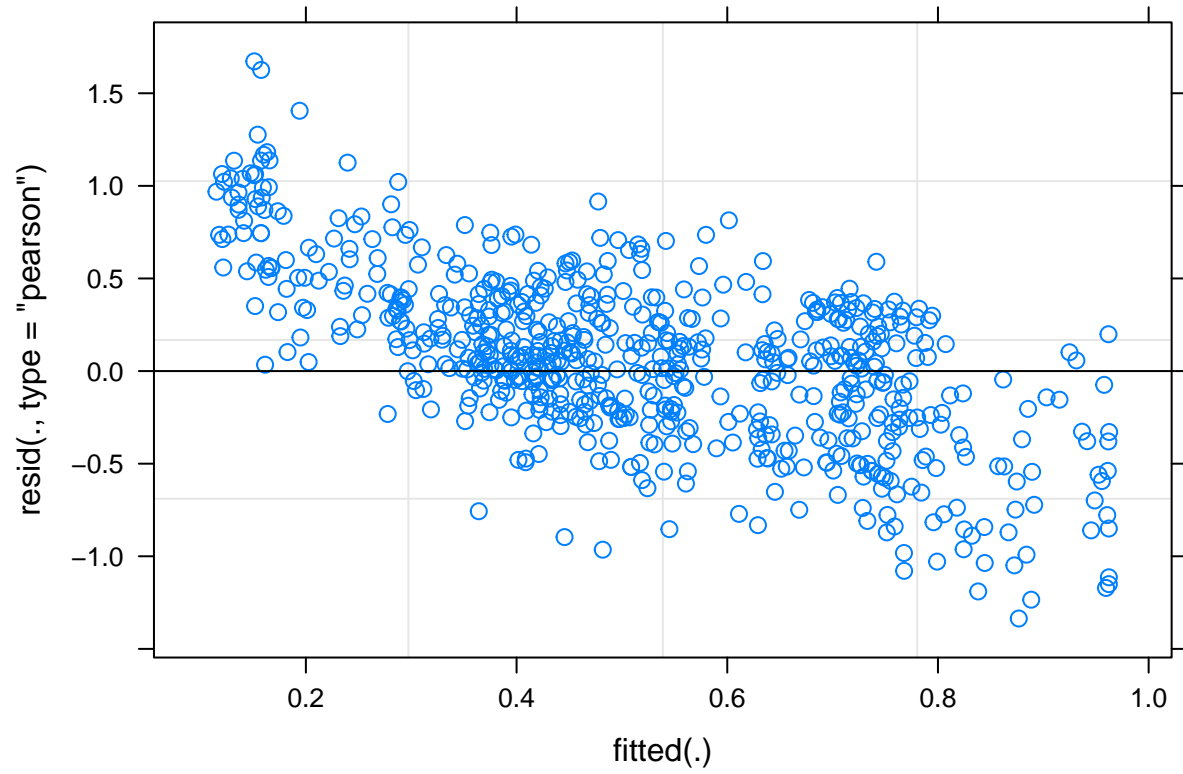
##
## Durbin-Watson test
##
## data: fit.glmm.re
## DW = 1.4285, p-value = 5.805e-14
## alternative hypothesis: true autocorrelation is greater than 0
plot(fit.plm.re$residuals, lag(fit.plm.re$residuals, -1))
```



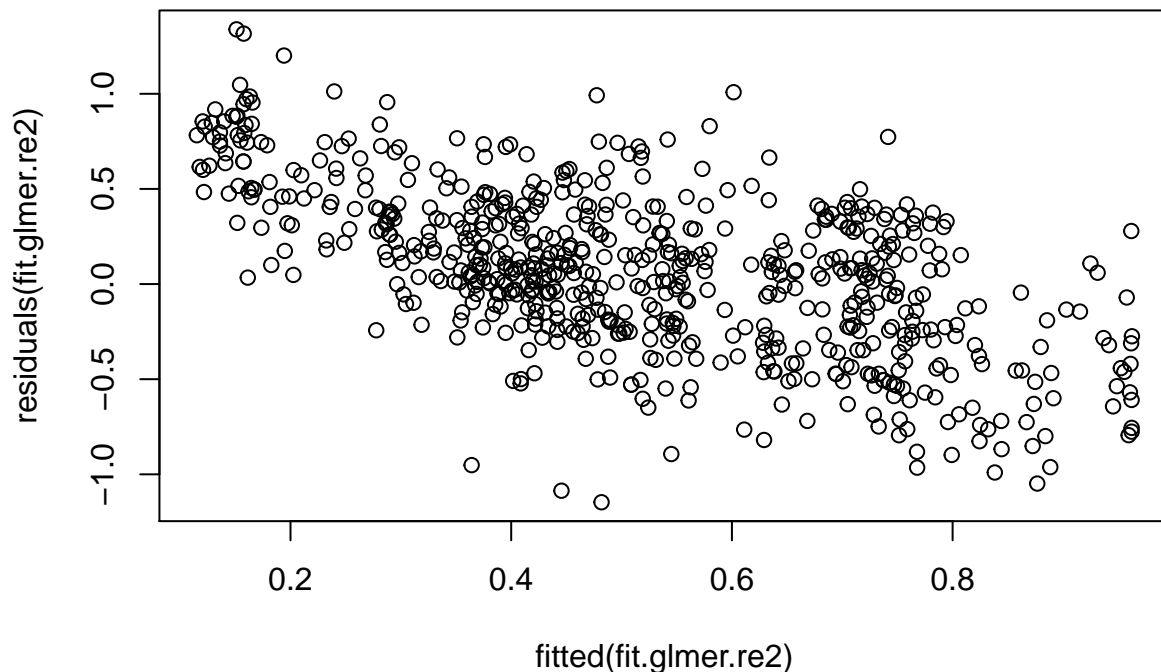
```
plot(fitted(fit.plm.re), residuals(fit.plm.re))
```



```
plot(fit.glmer.re2)
```



```
plot(fitted(fit.glmer.re2), residuals(fit.glmer.re2))
```



```
#plot(fitted(fit.glmm.re), residuals(fit.glmer.re)) # cannot extract residuals this way...
par(mfrow=c(1,1))
```

Listing 5 shows the GEE model. The results are similar to the previous model and also comparable across the three GEE models. Notably, the coefficient for SCIdeology changed the sign in the AR(1) model. However, the standard error is so high compared to the estimated coefficient that there probably is no underlying systematic association between SC and how the justices vote. Conversely, the MQ metric is significant and shows a high value for that Wald test  $10 \leq T_W \leq 21$ . On population average, a higher MQ value is negatively associated in margin to the percentage of left votes of justices.

```
fit.gee.in <- geeglm(Economics~SCIdeology+MQScore+Year,
                    data=df,id=JusticeName,family=binomial, corstr="independence")
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!
```

```
fit.gee.ex <- geeglm(Economics~SCIdeology+MQScore+Year,
                    data=df,id=JusticeName,family=binomial, corstr="exchangeable")
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!
```

```
fit.gee.ar <- geeglm(Economics~SCIdeology+MQScore+Year,
                    data=df,id=JusticeName,family=binomial, corstr="ar1")
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!
```

```
summary(fit.gee.in)
```

```
##
## Call:
## geeglm(formula = Economics ~ SCIdeology + MQScore + Year, family = binomial,
## data = df, id = JusticeName, corstr = "independence")
##
## Coefficients:
##             Estimate Std.err Wald Pr(>|W|)
## (Intercept)  0.202338  0.126539  2.557    0.110
## SCIdeology   0.182171  0.235093  0.600    0.438
## MQScore     -0.175192  0.034612 25.620 4.16e-07 ***
## Year        -0.008007  0.005192  2.379    0.123
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##             Estimate Std.err
## (Intercept)  0.1011 0.009576
##
## Correlation: Structure = independence Number of clusters: 38 Maximum cluster size: 35
```

```
summary(fit.gee.ex)
```

```
##
## Call:
## geeglm(formula = Economics ~ SCIdeology + MQScore + Year, family = binomial,
## data = df, id = JusticeName, corstr = "exchangeable")
##
## Coefficients:
##             Estimate Std.err Wald Pr(>|W|)
## (Intercept)  0.1499  0.1124  1.78    0.1823
## SCIdeology   0.3068  0.2338  1.72    0.1894
## MQScore     -0.1452  0.0244 35.43 2.6e-09 ***
## Year        -0.0122  0.0045  7.40  0.0065 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##             Estimate Std.err
## (Intercept)  0.102  0.0086
##
## Correlation: Structure = exchangeable Link = identity
##
## Estimated Correlation Parameters:
##             Estimate Std.err
## alpha       0.276  0.0627
## Number of clusters: 38 Maximum cluster size: 35
```

```
summary(fit.gee.ar)
```

```
##
## Call:
## geeglm(formula = Economics ~ SCIdeology + MQScore + Year, family = binomial,
## data = df, id = JusticeName, corstr = "ar1")
```

```
##
## Coefficients:
##           Estimate Std.err Wald Pr(>|W|)
## (Intercept)  0.31893  0.13704  5.42    0.02 *
## SCIdeology   0.00295  0.22818  0.00    0.99
## MQScore     -0.22603  0.03861 34.27  4.8e-09 ***
## Year        -0.00921  0.00616  2.24    0.13
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Estimated Scale Parameters:
##           Estimate Std.err
## (Intercept)   0.104  0.0123
##
## Correlation: Structure = ar1 Link = identity
##
## Estimated Correlation Parameters:
##           Estimate Std.err
## alpha        0.747  0.0429
## Number of clusters: 38 Maximum cluster size: 35

fit.gee.in.i <- geeglm(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year,
                      data=df,id=JusticeName,family=binomial, corstr="independence")

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

fit.gee.ex.i <- geeglm(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year,
                      data=df,id=JusticeName,family=binomial, corstr="exchangeable")

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

fit.gee.ar.i <- geeglm(Economics~SCIdeology+MQScore+Year+SCIdeology*Year+MQScore*Year,
                      data=df,id=JusticeName,family=binomial, corstr="ar1")

## Warning in eval(family$initialize): non-integer #successes in a binomial
## glm!

summary(fit.gee.in.i)

##
## Call:
## geeglm(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology *
##       Year + MQScore * Year, family = binomial, data = df, id = JusticeName,
##       corstr = "independence")
##
## Coefficients:
##           Estimate Std.err Wald Pr(>|W|)
## (Intercept)   0.26409  0.19016  1.93  0.1649
## SCIdeology     0.08380  0.33216  0.06  0.8008
## MQScore       -0.23658  0.07254 10.64  0.0011 **
## Year          -0.00957  0.00925  1.07  0.3009
## SCIdeology:Year 0.00425  0.01859  0.05  0.8190
## MQScore:Year   0.00374  0.00334  1.25  0.2631
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Estimated Scale Parameters:
##           Estimate Std.err
## (Intercept)    0.101 0.00938
##
## Correlation: Structure = independenceNumber of clusters: 38   Maximum cluster size: 35
```

```
summary(fit.gee.ex.i)
```

```
##
## Call:
## geeglm(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology *
##       Year + MQScore * Year, family = binomial, data = df, id = JusticeName,
##       corstr = "exchangeable")
##
```

```
## Coefficients:
##           Estimate Std.err Wald Pr(>|W|)
## (Intercept)    0.13445 0.17038 0.62 0.43006
## SCIdeology      0.36474 0.31172 1.37 0.24197
## MQScore        -0.18967 0.05352 12.56 0.00039 ***
## Year           -0.00538 0.00810 0.44 0.50645
## SCIdeology:Year -0.01522 0.01557 0.96 0.32842
## MQScore:Year    0.00197 0.00222 0.78 0.37600
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

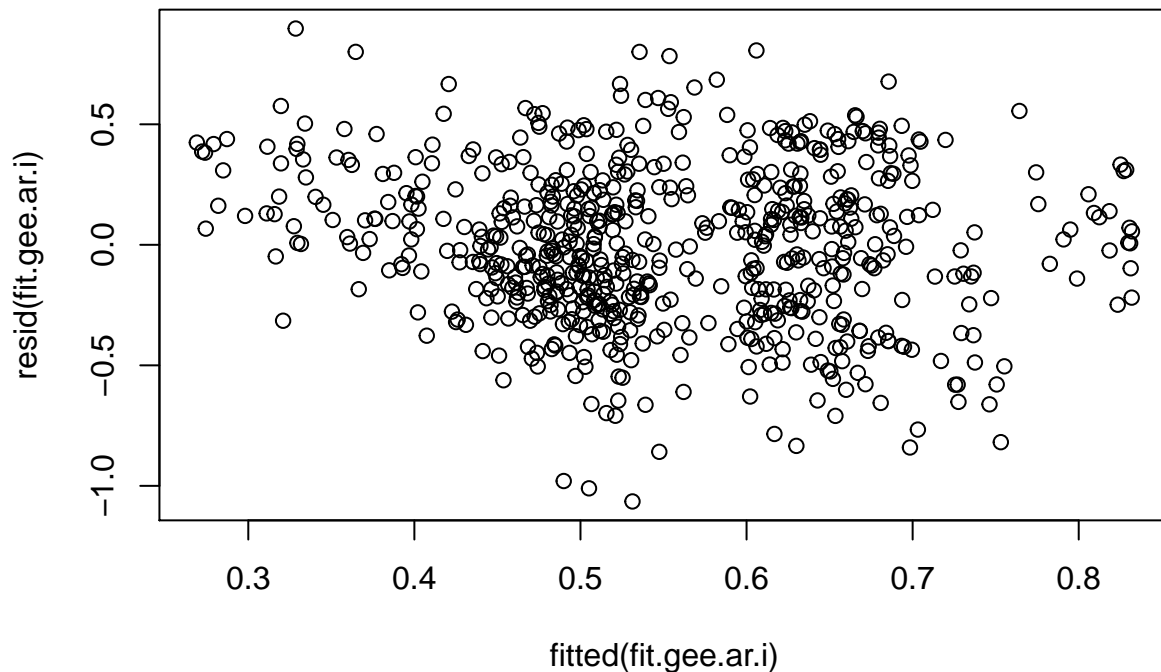
```
## Estimated Scale Parameters:
##           Estimate Std.err
## (Intercept)    0.101 0.00753
##
## Correlation: Structure = exchangeable Link = identity
##
## Estimated Correlation Parameters:
##           Estimate Std.err
## alpha      0.284 0.0604
## Number of clusters: 38   Maximum cluster size: 35
```

```
summary(fit.gee.ar.i)
```

```
##
## Call:
## geeglm(formula = Economics ~ SCIdeology + MQScore + Year + SCIdeology *
##       Year + MQScore * Year, family = binomial, data = df, id = JusticeName,
##       corstr = "ar1")
##
```

```
## Coefficients:
##           Estimate Std.err Wald Pr(>|W|)
## (Intercept)    0.401590 0.186026 4.66 0.031 *
## SCIdeology     -0.106369 0.283861 0.14 0.708
## MQScore        -0.330873 0.073091 20.49 6e-06 ***
## Year           -0.009041 0.009912 0.83 0.362
## SCIdeology:Year 0.000697 0.018996 0.00 0.971
## MQScore:Year    0.006261 0.003510 3.18 0.074 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Estimated Scale Parameters:
##           Estimate Std.err
## (Intercept)   0.105  0.0124
##
## Correlation: Structure = ar1 Link = identity
##
## Estimated Correlation Parameters:
##           Estimate Std.err
## alpha      0.753  0.0389
## Number of clusters: 38 Maximum cluster size: 35
plot(fitted(fit.gee.ar.i), resid(fit.gee.ar.i))
```



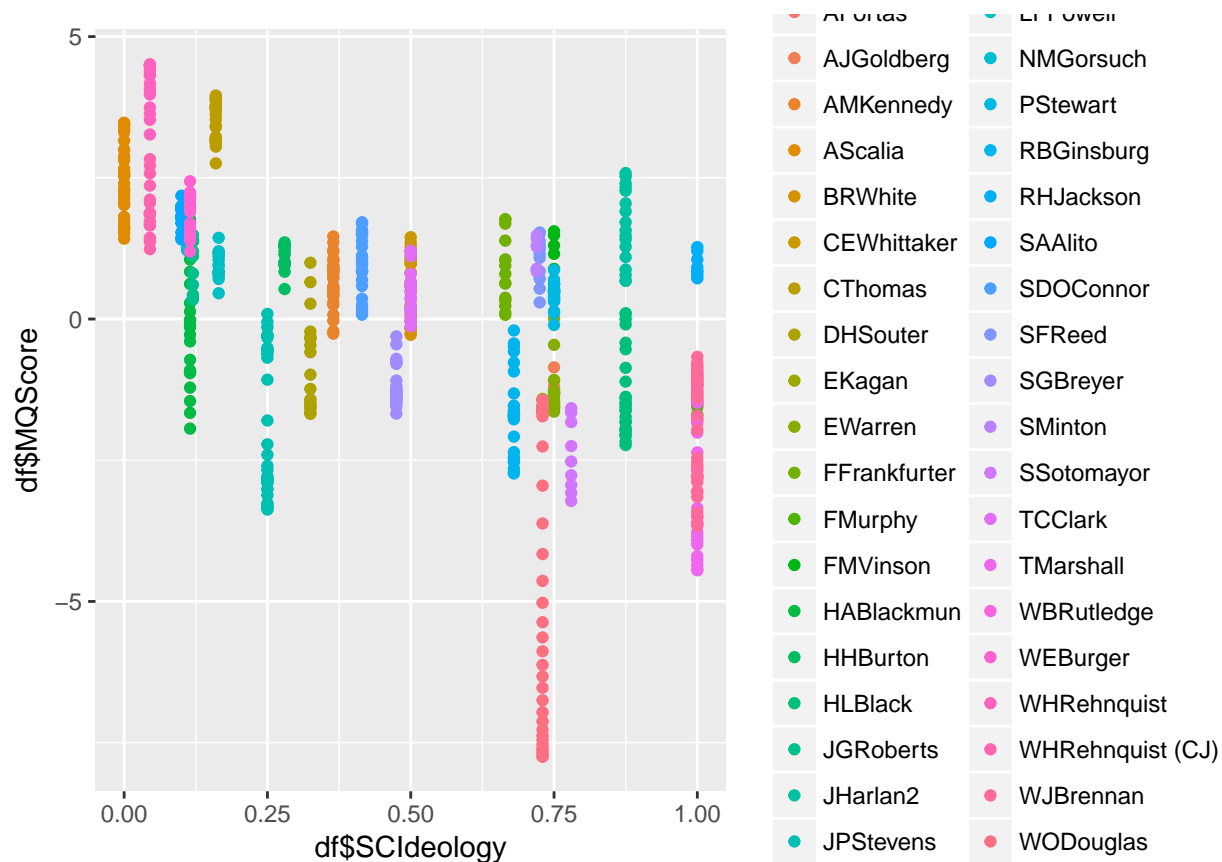
The GEE model with AR correlation structure is a good fit (and for a paper, you would only report this one in particular), because it deals with the assumed autocorrelation and we because are not interested in the unit-level effects. Rather, we are interested in population average effect across all justices, whether they are getting more mild with time. Our covariate of main interest SC does not show such an effect, but the MQ covariate does, including the interaction effect at  $P(> |W|) = 0.074$ ). Since both are supposed to capture the political ideology, a further inquiry should look at how both metrics are derived. Listing 6 shows that there is a mild correlation between the two.

```
cor(df$SCIdeology, df$MQScore)

## [1] -0.56

ggplot(df, aes(df$SCIdeology, df$MQScore)) + geom_point(aes(colour=as.factor(JusticeName)))
```





Ultimately, I am not convinced that the hypothesis holds. For the model specification, there are probably other variables that are omitted skewing the results. Also, the basic OLS model is misleading in this case. It would be interested to hear to what conclusions the other participants came. Cheers.