CSSS 512 HW 3

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Problem 1

Part a

```
#process data
house <- read_csv("statehouse.csv") %>%
  filter(GovCycle == 1, #gov cycle needs to be 2010, 2014, 2018...
         HouseTerm == 2) %>% #2 yr house term only
  arrange(State, Year) %>% #arrange by State, then year within States
  group_by(State) %>% #group rows by State for lagging
  mutate(DemHouseShareL1 = lag(DemHouseShare, 1), #use dplyr::lag with properly ordered and grouped tbl
         DemHouseShareL2 = lag(DemHouseShare, 2),
         DemHouseShareL3 = lag(DemHouseShare, 3),
         DemHouseShareL4 = lag(DemHouseShare, 4))
```

```
## Parsed with column specification:
## cols(
##   .default = col_integer(),
##   State = col_character(),
##   Statename = col_character(),
##   Unemployment = col_double(),
##   DemHouseShare = col_double(),
##   RepHouseShare = col_double(),
##   DemSenateShare = col_double(),
##   RepSenateShare = col_double(),
##   unemDeviation = col_double(),
##   PresUnem = col_double(),
##   GovUnem = col_double()
## )
```

```
## See spec(...) for full column specifications.
```

```
#double check work using dplyr::lag()
#house %>%
#  select(State, Year, DemHouseShare, DemHouseShareL1, DemHouseShareL2, DemHouseShareL3, DemHouseShareL
#  View()

#28 states
length(unique(house$State))
```

```
## [1] 28
```

```
#20 periods
length(unique(house$Year))
```

```
## [1] 20
```

Part b

Looks like AR(1) processes in most states. Some of the observed time-series look non-stationary given no reversion to a mean over the full length of periods. Other States' series, however, look like stationarity assumption is less problematic. The nonstationary conclusion is also supported by a fair number `adf.test` and `PP.test` p-values falling outside of the conventional p<.05 threshold, though these are weak tests.

States with clear change over the period show decreashing democratic vote shares over the full set of periods, though there are states like New York which oppose this direction. The IPS tests suggest that we could consider the panel as stationary with individual intercepts and trends (i.e. enough of the panel is stationary with these adjustments is what I glean from the test, at least based on my understanding of what it's testing for). While region-specific trends are not a perfect solution, we can't identify a model with case-specific trends so the M2 specification is probably the best we can do for modeling the temporal dynamics enough to achieve stationarity without resorting to an integrated model.

```
#make some file structure for output
if(!dir.exists("output")){
  dir.create("output")
  dir.create("output/ts")
  dir.create("output/acf")
  dir.create("output/pacf")
}

#empty obj for unit root test results
unitroot.tbl <- NULL

#iterate through states
for(state in unique(house$State)){

  #pull the state's ts
  ts <- house %>%
    filter(State == state) %>%
    pull(DemHouseShare)

  #make it ts class
  ts <- ts(ts, start = 1978, end = 2016, frequency = 1/2)

  #plot the ts
  TS <- autoplot(ts) +
    scale_y_continuous(labels = scales::percent) +
    labs(title = paste0("Democratic House Share for ", house$Statename[house$State == state])) +
    theme_minimal()

  #plot the ACF
  ACF <- ggAcf(ts) +
    labs(title = paste0("ACF for ", house$Statename[house$State == state])) +
    theme_minimal()

  #plot the PACF
  PACF <- ggPacf(ts) +
    labs(title = paste0("PACF for ", house$Statename[house$State == state])) +
    theme_minimal()

  #rum ADF test, parse results to row
  ADF <- tseries::adf.test(ts)
```

```r
  ADF.row <- data.frame(state = state,
                        test = "ADF",
                        statistic = ADF[['statistic']],
                        parameter = ADF[['parameter']],
                        p.value = ADF[['p.value']],
                        stringsAsFactors = F)

  #run PP test, parse results to row
  PP <- PP.test(ts)
  PP.row <- data.frame(state = state,
                       test = "PP",
                       statistic = PP[['statistic']],
                       parameter = PP[['parameter']],
                       p.value = PP[['p.value']],
                       stringsAsFactors = F)

  #write graphics to pdf
  ggsave(TS, filename = paste0("./output/ts/", state, "_ts.pdf"),
         width = 8, height = 6, dpi = 300)
  ggsave(ACF, filename = paste0("./output/acf/", state, "_acf.pdf"),
         width = 8, height = 6, dpi = 300)
  ggsave(PACF, filename = paste0("./output/pacf/", state, "_pacf.pdf"),
         width = 8, height = 6, dpi = 300)

  #add row to unit root tbl
  unitroot.tbl <- bind_rows(unitroot.tbl, ADF.row, PP.row)
}
```

```
## Warning in tseries::adf.test(ts): p-value greater than printed p-value

## Warning in tseries::adf.test(ts): p-value smaller than printed p-value
```

```r
#panel unit root test
ts <- with(house, data.frame(split(DemHouseShare, as.character(State))))
purtest(ts, pmax = 4, exo = "intercept", house_p, test = "ips")
```

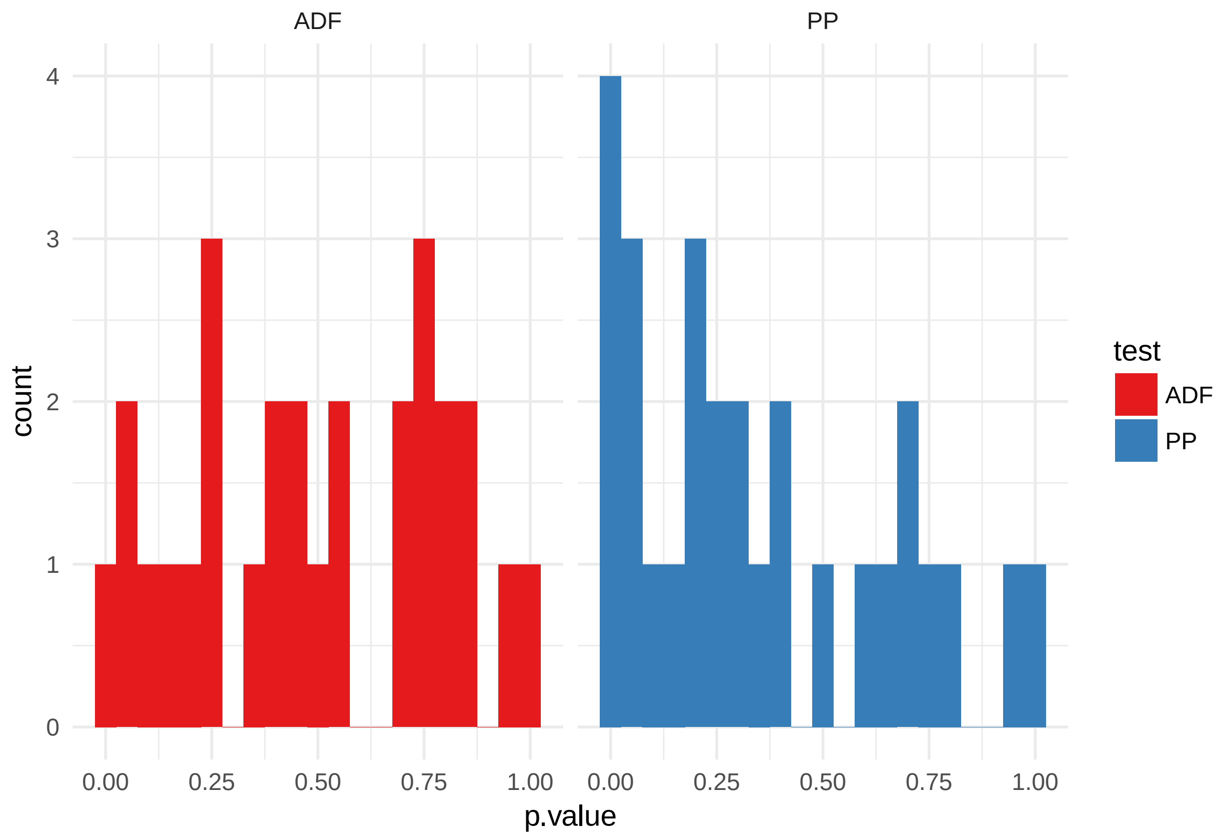
```
##
##  Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts)
##
## data:  ts
## z = -1.0999, p-value = 0.1357
## alternative hypothesis: stationarity
```

```r
purtest(ts, pmax = 4, exo = "trend", house_p, test = "ips")
```

```
##
##  Im-Pesaran-Shin Unit-Root Test (ex. var.: Individual Intercepts
##  and Trend)
##
## data:  ts
## z = -5.6466, p-value = 8.182e-09
## alternative hypothesis: stationarity
```

```r
#write unit root tbl to storage
write_csv(unitroot.tbl, "output/unitroot_tests.csv")
```

```r
#plot unit root p.val dist
ggplot(unitroot.tbl, aes(x = p.value, fill = test)) +
  facet_wrap(~ test) +
  geom_histogram(binwidth = .05) +
  theme_minimal() +
  scale_fill_brewer(palette = "Set1")
```



Part c

The “b” specification where the dynamics are modeled as AR(1) with covariates appears to fit best according to BIC, which penalizes more complicated specifications like other information criteria.

```r
house <- groupedData(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattail

#no dynamics, just covariates + state random effect
re_m1_a <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails,
            random = ~ 1,
            data = house)
summary(re_m1_a)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -870.4684 -835.9311 443.2342
##
## Random effects:
```

```
##  Formula: ~1 | State
##         (Intercept)   Residual
## StdDev:   0.1450158 0.09578092
##
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value   Std.Error  DF   t-value p-value
## (Intercept)      0.5300282 0.027710483 527 19.127355  0.0000
## PartisanMidterm -0.0258120 0.005949586 527 -4.338447  0.0000
## PresUnem        -0.0061882 0.002157174 527 -2.868676  0.0043
## GovUnem         -0.0014973 0.002214078 527 -0.676268  0.4992
## PresCoattails    0.0308660 0.008210479 527  3.759343  0.0002
## GovCoattails    -0.0009114 0.010272567 527 -0.088722  0.9293
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt
## PartisanMidterm  0.002
## PresUnem         0.010 -0.073
## GovUnem         -0.012 -0.008  0.101
## PresCoattails    0.012  0.009 -0.096  0.084
## GovCoattails     0.008  0.257  0.040  0.130  0.014
##
## Standardized Within-Group Residuals:
##          Min           Q1          Med           Q3          Max
## -5.115586850 -0.458111766  0.004553713  0.577798973  3.391666970
##
## Number of Observations: 560
## Number of Groups: 28
```

```r
#AR(1)
re_m1_b <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails,
            random = ~ 1,
            correlation = corARMA(p = 1, q = 0),
            data = house)
summary(re_m1_b)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -1478.543 -1439.689 748.2716
##
## Random effects:
##  Formula: ~1 | State
##          (Intercept)  Residual
## StdDev: 2.003284e-05 0.1863717
##
## Correlation Structure: AR(1)
##  Formula: ~1 | State
##  Parameter estimate(s):
##       Phi
## 0.9515831
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value   Std.Error  DF   t-value p-value
## (Intercept)      0.5320991 0.029103606 527 18.282925  0.0000
## PartisanMidterm -0.0173082 0.002673649 527 -6.473609  0.0000
## PresUnem        -0.0027568 0.001186136 527 -2.324206  0.0205
## GovUnem          0.0000452 0.001165194 527  0.038778  0.9691
```

```
## PresCoattails    0.0238158 0.003843819 527  6.195874  0.0000
## GovCoattails     0.0003370 0.004607963 527  0.073143  0.9417
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt
## PartisanMidterm -0.037
## PresUnem         0.040 -0.134
## GovUnem          0.000  0.004  0.054
## PresCoattails    0.054 -0.132  0.234  0.083
## GovCoattails    -0.002  0.265  0.000  0.206 -0.096
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.14817288 -0.71077651  0.02527817  0.49041596  3.47027645
##
## Number of Observations: 560
## Number of Groups: 28
```

```
#MA(1)
re_m1_c <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails,
            random = ~ 1,
            correlation = corARMA(p = 0, q = 1),
            data = house)
summary(re_m1_c)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -1178.021 -1139.167 598.0106
##
## Random effects:
##  Formula: ~1 | State
##         (Intercept)   Residual
## StdDev:   0.1443078 0.08610247
##
## Correlation Structure: ARMA(0,1)
##  Formula: ~1 | State
##  Parameter estimate(s):
##    Theta1
## 0.6518423
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value   Std.Error  DF   t-value p-value
## (Intercept)      0.5300393 0.027722381 527 19.119545  0.0000
## PartisanMidterm -0.0178216 0.003776712 527 -4.718821  0.0000
## PresUnem        -0.0065010 0.001600239 527 -4.062545  0.0001
## GovUnem         -0.0005158 0.001668318 527 -0.309180  0.7573
## PresCoattails    0.0291540 0.005731799 527  5.086362  0.0000
## GovCoattails    -0.0014326 0.006799154 527 -0.210709  0.8332
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt
## PartisanMidterm -0.001
## PresUnem         0.017 -0.203
## GovUnem         -0.009  0.005  0.010
## PresCoattails    0.013 -0.082  0.187  0.077
## GovCoattails     0.003  0.216 -0.028  0.203 -0.091
##
```

```
## Standardized Within-Group Residuals:
##        Min         Q1        Med         Q3        Max
## -5.6243348 -0.4862232 -0.0137772  0.6245002  3.7564173
##
## Number of Observations: 560
## Number of Groups: 28
```

```r
#ARMA(1,1)
re_m1_d <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails,
            random = ~ 1,
            correlation = corARMA(p = 1, q = 1),
            data = house)
summary(re_m1_d)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -1485.489 -1442.317 752.7443
##
## Random effects:
##  Formula: ~1 | State
##          (Intercept)  Residual
## StdDev: 1.651642e-05 0.1879519
##
## Correlation Structure: ARMA(1,1)
##  Formula: ~1 | State
##  Parameter estimate(s):
##       Phi1     Theta1
##  0.9667285 -0.1594405
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value   Std.Error  DF   t-value p-value
## (Intercept)      0.5316099 0.030815354 527 17.251461  0.0000
## PartisanMidterm -0.0172671 0.002833053 527 -6.094870  0.0000
## PresUnem        -0.0020871 0.001196125 527 -1.744903  0.0816
## GovUnem         -0.0000834 0.001188121 527 -0.070237  0.9440
## PresCoattails    0.0247001 0.003981277 527  6.204077  0.0000
## GovCoattails    -0.0000794 0.004784512 527 -0.016602  0.9868
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt
## PartisanMidterm -0.038
## PresUnem         0.034 -0.115
## GovUnem          0.002 -0.001  0.074
## PresCoattails    0.055 -0.123  0.173  0.094
## GovCoattails    -0.001  0.266  0.020  0.194 -0.072
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.12509458 -0.70194928  0.02445651  0.48931483  3.45591960
##
## Number of Observations: 560
## Number of Groups: 28
```

```r
#AR(1) appears to fit best. The MA(1) contribution is small, and higher-order
#autoregression also does not seem to be present
```

Part d

Similarly, after including region and year fixed effects in addition to region-specific trends, the AR(1) "b" specification appears to fit best according to BIC.

```
#M1 + region specific trends
house <- groupedData(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattail

#no dynamics, just covariates + state random effect
re_m2_a <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Ye
            random = ~ 1,
            data = house)
summary(re_m2_a)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -1266.713 -1202.146 648.3563
##
## Random effects:
##  Formula: ~1 | State
##         (Intercept)   Residual
## StdDev:   0.1249249 0.06188893
##
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value Std.Error  DF    t-value p-value
## (Intercept)     -0.663882 0.9887891 523  -0.671409  0.5023
## PartisanMidterm -0.016406 0.0039055 523  -4.200712  0.0000
## PresUnem         0.000613 0.0014641 523   0.418606  0.6757
## GovUnem          0.001577 0.0014551 523   1.084097  0.2788
## PresCoattails    0.029972 0.0053065 523   5.648087  0.0000
## GovCoattails     0.006267 0.0066871 523   0.937137  0.3491
## Year             0.000664 0.0004942 523   1.344384  0.1794
## Midwest          7.751154 1.3044261  24   5.942195  0.0000
## South           27.349355 1.3896088  24  19.681333  0.0000
## West             1.118250 1.3032560  24   0.858043  0.3994
## Year:Midwest    -0.003978 0.0006520 523  -6.101861  0.0000
## Year:South      -0.013730 0.0006945 523 -19.768252  0.0000
## Year:West       -0.000663 0.0006514 523  -1.017693  0.3093
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt GvCttl Year   Midwst
## PartisanMidterm  0.096
## PresUnem         0.073 -0.018
## GovUnem          0.029  0.013  0.125
## PresCoattails    0.000  0.007 -0.096  0.084
## GovCoattails     0.079  0.272  0.071  0.137  0.013
## Year            -0.999 -0.096 -0.074 -0.030  0.001 -0.079
## Midwest         -0.744 -0.012  0.037  0.095  0.005 -0.033  0.743
## South           -0.697 -0.010  0.063  0.006 -0.006 -0.027  0.696  0.534
## West            -0.740 -0.005  0.096 -0.018 -0.012 -0.007  0.739  0.566
## Year:Midwest     0.743  0.012 -0.036 -0.095 -0.005  0.033 -0.744 -0.999
## Year:South       0.696  0.010 -0.063 -0.006  0.006  0.027 -0.697 -0.533
## Year:West        0.739  0.005 -0.096  0.019  0.012  0.007 -0.740 -0.566
##                 South  West   Yr:Mdw Yr:Sth
## PartisanMidterm
```

```
## PresUnem
## GovUnem
## PresCoattails
## GovCoattails
## Year
## Midwest
## South
## West             0.537
## Year:Midwest    -0.533 -0.566
## Year:South      -0.999 -0.536  0.534
## Year:West       -0.536 -0.999  0.566  0.537
##
## Standardized Within-Group Residuals:
##          Min           Q1          Med           Q3          Max
## -3.869727154 -0.566519327  0.003317872  0.607891381  5.302718180
##
## Number of Observations: 560
## Number of Groups: 28
```

```r
#AR(1)
re_m2_b <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
            random = ~ 1,
            correlation = corARMA(p = 1, q = 0),
            data = house)
summary(re_m2_b)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -1493.168 -1424.297 762.5841
##
## Random effects:
##  Formula: ~1 | State
##         (Intercept) Residual
## StdDev:   0.1216014 0.070748
##
## Correlation Structure: AR(1)
##  Formula: ~1 | State
##  Parameter estimate(s):
##       Phi
## 0.6780037
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value Std.Error  DF   t-value p-value
## (Intercept)       0.222655 1.9292147 523  0.115412  0.9082
## PartisanMidterm -0.017601 0.0027449 523 -6.412234  0.0000
## PresUnem        -0.002511 0.0011925 523 -2.105462  0.0357
## GovUnem          0.000213 0.0011841 523  0.179471  0.8576
## PresCoattails    0.023498 0.0038977 523  6.028700  0.0000
## GovCoattails     0.001030 0.0047335 523  0.217557  0.8279
## Year             0.000221 0.0009652 523  0.228563  0.8193
## Midwest          6.699663 2.5518836  24  2.625380  0.0148
## South           26.109620 2.7267721  24  9.575285  0.0000
## West            -0.118461 2.5509932  24 -0.046437  0.9633
## Year:Midwest    -0.003453 0.0012768 523 -2.704439  0.0071
## Year:South      -0.013111 0.0013643 523 -9.610358  0.0000
```

```
## Year:West       -0.000041 0.0012763 523 -0.032473  0.9741
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt GvCttl Year   Midwst
## PartisanMidterm -0.006
## PresUnem        -0.015 -0.122
## GovUnem         -0.003  0.003  0.059
## PresCoattails   -0.046 -0.115  0.188  0.083
## GovCoattails     0.010  0.264  0.010  0.196 -0.087
## Year            -1.000  0.006  0.015  0.003  0.046 -0.010
## Midwest         -0.755 -0.002  0.024  0.042  0.007  0.009  0.754
## South           -0.706 -0.001  0.027  0.023  0.006  0.011  0.706  0.535
## West            -0.755 -0.002  0.038  0.002  0.006  0.009  0.755  0.571
## Year:Midwest     0.754  0.002 -0.024 -0.042 -0.007 -0.009 -0.755 -1.000
## Year:South       0.706  0.001 -0.027 -0.023 -0.006 -0.011 -0.706 -0.535
## Year:West        0.755  0.002 -0.038 -0.002 -0.006 -0.008 -0.755 -0.571
##                 South  West   Yr:Mdw Yr:Sth
## PartisanMidterm
## PresUnem
## GovUnem
## PresCoattails
## GovCoattails
## Year
## Midwest
## South
## West             0.535
## Year:Midwest    -0.535 -0.571
## Year:South      -1.000 -0.535  0.535
## Year:West       -0.535 -1.000  0.571  0.535
##
## Standardized Within-Group Residuals:
##          Min           Q1          Med           Q3          Max
## -3.073788053 -0.507209793 -0.003192118  0.531633516  4.643755585
##
## Number of Observations: 560
## Number of Groups: 28
```

```r
#MA(1)
re_m2_c <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
            random = ~ 1,
            correlation = corARMA(p = 0, q = 1),
            data = house)
summary(re_m2_c)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC   logLik
##   -1423.988 -1355.116 727.9938
##
## Random effects:
##  Formula: ~1 | State
##         (Intercept)   Residual
## StdDev:   0.1246408 0.06013472
##
## Correlation Structure: ARMA(0,1)
##  Formula: ~1 | State
```

```
##  Parameter estimate(s):
##    Theta1
## 0.4915541
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                      Value Std.Error  DF    t-value p-value
## (Intercept)     -0.652655 1.2163327 523  -0.536576  0.5918
## PartisanMidterm -0.017788 0.0030064 523  -5.916746  0.0000
## PresUnem        -0.002538 0.0012862 523  -1.973156  0.0490
## GovUnem          0.000679 0.0013128 523   0.517571  0.6050
## PresCoattails    0.027213 0.0043427 523   6.266490  0.0000
## GovCoattails     0.001910 0.0054153 523   0.352744  0.7244
## Year             0.000659 0.0006082 523   1.083599  0.2790
## Midwest          7.356829 1.6108638  24   4.567009  0.0001
## South           26.894346 1.7184002  24  15.650805  0.0000
## West             0.471431 1.6096884  24   0.292871  0.7721
## Year:Midwest    -0.003782 0.0008055 523  -4.694712  0.0000
## Year:South      -0.013503 0.0008593 523 -15.714323  0.0000
## Year:West       -0.000339 0.0008049 523  -0.420978  0.6739
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt GvCttl Year   Midwst
## PartisanMidterm  0.030
## PresUnem         0.033 -0.135
## GovUnem          0.007  0.008  0.051
## PresCoattails   -0.033 -0.078  0.121  0.084
## GovCoattails     0.040  0.245  0.014  0.186 -0.076
## Year            -0.999 -0.030 -0.033 -0.007  0.033 -0.041
## Midwest         -0.751 -0.009  0.033  0.073  0.012 -0.009  0.750
## South           -0.704 -0.009  0.046  0.015  0.008 -0.009  0.703  0.535
## West            -0.750 -0.010  0.071 -0.011  0.007 -0.002  0.749  0.569
## Year:Midwest     0.751  0.009 -0.032 -0.073 -0.012  0.009 -0.751 -0.999
## Year:South       0.703  0.009 -0.045 -0.015 -0.008  0.010 -0.704 -0.534
## Year:West        0.749  0.010 -0.071  0.011 -0.007  0.003 -0.750 -0.569
##                 South  West   Yr:Mdw Yr:Sth
## PartisanMidterm
## PresUnem
## GovUnem
## PresCoattails
## GovCoattails
## Year
## Midwest
## South
## West             0.536
## Year:Midwest    -0.534 -0.569
## Year:South      -0.999 -0.535  0.535
## Year:West       -0.535 -0.999  0.569  0.536
##
## Standardized Within-Group Residuals:
##          Min           Q1          Med           Q3          Max
## -4.039528945 -0.597789405 -0.001535577  0.612732701  5.330058002
##
## Number of Observations: 560
## Number of Groups: 28
```

```r
#ARMA(1,1)
re_m2_d <- lme(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
            random = ~ 1,
            correlation = corARMA(p = 1, q = 1),
            data = house)
summary(re_m2_d)
```

```
## Linear mixed-effects model fit by REML
##  Data: house
##         AIC       BIC  logLik
##   -1492.238 -1419.062 763.119
##
## Random effects:
##  Formula: ~1 | State
##         (Intercept)   Residual
## StdDev:   0.1205712 0.07297499
##
## Correlation Structure: ARMA(1,1)
##  Formula: ~1 | State
##  Parameter estimate(s):
##        Phi1      Theta1
##  0.74467028 -0.09231362
## Fixed effects: DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +      GovCoatta
##                     Value Std.Error  DF   t-value p-value
## (Intercept)      0.381789 2.0436040 523  0.186821  0.8519
## PartisanMidterm -0.017588 0.0027924 523 -6.298660  0.0000
## PresUnem        -0.002251 0.0011872 523 -1.896134  0.0585
## GovUnem          0.000150 0.0011816 523  0.126948  0.8990
## PresCoattails    0.023663 0.0039296 523  6.021756  0.0000
## GovCoattails     0.000837 0.0047574 523  0.175981  0.8604
## Year             0.000141 0.0010225 523  0.137756  0.8905
## Midwest          6.578083 2.7030472  24  2.433580  0.0228
## South           25.969896 2.8884985  24  8.990794  0.0000
## West            -0.153773 2.7020075  24 -0.056910  0.9551
## Year:Midwest    -0.003392 0.0013524 523 -2.508082  0.0124
## Year:South      -0.013041 0.0014452 523 -9.023701  0.0000
## Year:West       -0.000023 0.0013519 523 -0.017162  0.9863
##  Correlation:
##                 (Intr) PrtsnM PrsUnm GovUnm PrsCtt GvCttl Year   Midwst
## PartisanMidterm -0.008
## PresUnem        -0.018 -0.114
## GovUnem         -0.004  0.001  0.068
## PresCoattails   -0.044 -0.113  0.168  0.087
## GovCoattails     0.007  0.265  0.018  0.192 -0.077
## Year            -1.000  0.008  0.018  0.004  0.044 -0.007
## Midwest         -0.755 -0.002  0.022  0.040  0.006  0.010  0.755
## South           -0.706  0.000  0.025  0.024  0.005  0.013  0.706  0.535
## West            -0.755 -0.001  0.034  0.004  0.005  0.010  0.755  0.571
## Year:Midwest     0.755  0.002 -0.022 -0.040 -0.006 -0.010 -0.755 -1.000
## Year:South       0.706  0.000 -0.025 -0.024 -0.005 -0.013 -0.706 -0.535
## Year:West        0.755  0.001 -0.034 -0.004 -0.005 -0.010 -0.755 -0.571
##                 South  West   Yr:Mdw Yr:Sth
## PartisanMidterm
## PresUnem
```

```
## GovUnem
## PresCoattails
## GovCoattails
## Year
## Midwest
## South
## West              0.535
## Year:Midwest    -0.535 -0.571
## Year:South      -1.000 -0.535  0.535
## Year:West       -0.535 -1.000  0.571  0.535
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -2.86387520 -0.50377863 -0.01518369  0.54601374  4.56200241
##
## Number of Observations: 560
## Number of Groups: 28
```

```
#model b (AR(1)) is best
```

Part e

The "b" specification with one lagged dependent variable (i.e. AR(1)) appears to fit best according to AIC.

```
#obtained from
#https://stackoverflow.com/questions/46186527/how-to-calculate-bic-and-aic-for-a-gmm-model-in-r-using-p
AIC_adj <- function(mod){
  # Number of observations
  n.N   <- nrow(mod$model)
  # Residuals vector
  u.hat <- residuals(mod)
  # Variance estimation
  s.sq  <- log( (sum(u.hat^2)/(n.N)))
  # Number of parameters (incl. constant) + one additional for variance estimation
  p     <-  length(coef(mod)) + 1

  # Note: minus sign cancels in log likelihood
  aic <- 2*p  +  n.N * (  log(2*pi) + s.sq  + 1 )

  return(aic)
}

house_p <- pdata.frame(house, index = "State")

fe_m1_a <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails,  da
summary(fe_m1_a)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails, data = house_p, effect = "individual",
##     model = "within")
##
```

```
## Balanced Panel: n = 28, T = 20, N = 560
##
## Residuals:
##        Min.     1st Qu.      Median     3rd Qu.        Max.
## -0.49495161 -0.04288217  0.00026928  0.05338935  0.32449488
##
## Coefficients:
##                   Estimate Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.0258140  0.0059496 -4.3388 1.718e-05 ***
## PresUnem        -0.0062685  0.0021579 -2.9048 0.0038287 **
## GovUnem         -0.0014324  0.0022159 -0.6464 0.5183071
## PresCoattails    0.0309205  0.0082106  3.7659 0.0001846 ***
## GovCoattails    -0.0010022  0.0102734 -0.0975 0.9223279
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5.2359
## Residual Sum of Squares: 4.8347
## R-Squared:      0.076635
## Adj. R-Squared: 0.020567
## F-statistic: 8.74771 on 5 and 527 DF, p-value: 5.5268e-08
```

```r
AIC_adj(fe_m1_a)
```

```
## [1] -1059.976
```

```r
fe_m1_b <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Der
summary(fe_m1_b)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails + DemHouseShareL1, data = house_p,
##     effect = "individual", model = "within")
##
## Balanced Panel: n = 28, T = 19, N = 532
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -0.2890218 -0.0280934  0.0012287  0.0318992  0.3199008
##
## Coefficients:
##                    Estimate  Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.03193827  0.00361433 -8.8366 < 2.2e-16 ***
## PresUnem        -0.00344837  0.00126173 -2.7331  0.006498 **
## GovUnem          0.00041925  0.00130732  0.3207  0.748580
## PresCoattails    0.01197869  0.00475685  2.5182  0.012108 *
## GovCoattails     0.00825145  0.00626130  1.3178  0.188160
## DemHouseShareL1  0.79523860  0.02623142 30.3163 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4.8065
## Residual Sum of Squares: 1.508
```

```
## R-Squared:      0.68626
## Adj. R-Squared: 0.66547
## F-statistic: 181.554 on 6 and 498 DF, p-value: < 2.22e-16
```

```r
AIC_adj(fe_m1_b)
```

```
## [1] -1596.891
```

```r
fe_m1_c <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Dem
summary(fe_m1_c)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails + DemHouseShareL1 + DemHouseShareL2,
##     data = house_p, effect = "individual", model = "within")
##
## Balanced Panel: n = 28, T = 18, N = 504
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -0.2470322 -0.0277737  0.0040423  0.0330251  0.3243727
##
## Coefficients:
##                   Estimate  Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.02990000  0.00367183 -8.1431 3.511e-15 ***
## PresUnem        -0.00356776  0.00131527 -2.7126  0.006922 **
## GovUnem          0.00089512  0.00134650  0.6648  0.506519
## PresCoattails    0.01758159  0.00550056  3.1963  0.001486 **
## GovCoattails     0.01014738  0.00631437  1.6070  0.108721
## DemHouseShareL1  0.66917876  0.04292171 15.5907 < 2.2e-16 ***
## DemHouseShareL2  0.14692632  0.04453735  3.2989  0.001044 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4.4732
## Residual Sum of Squares: 1.4247
## R-Squared:      0.68149
## Adj. R-Squared: 0.6584
## F-statistic: 143.356 on 7 and 469 DF, p-value: < 2.22e-16
```

```r
AIC_adj(fe_m1_c)
```

```
## [1] -1511.476
```

```r
fe_m1_d <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Dem
summary(fe_m1_d)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails + DemHouseShareL1 + DemHouseShareL2 +
##     DemHouseShareL3, data = house_p, effect = "individual", model = "within")
##
## Balanced Panel: n = 28, T = 17, N = 476
```

```
##
## Residuals:
##       Min.    1st Qu.     Median    3rd Qu.       Max.
## -0.2435687 -0.0285582  0.0025573  0.0330719  0.3227652
##
## Coefficients:
##                    Estimate  Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.03239126  0.00389932 -8.3069 1.226e-15 ***
## PresUnem        -0.00318589  0.00151548 -2.1022   0.03610 *
## GovUnem          0.00061453  0.00157916  0.3892   0.69735
## PresCoattails    0.01617449  0.00552760  2.9261   0.00361 **
## GovCoattails     0.00867135  0.00656659  1.3205   0.18735
## DemHouseShareL1  0.64600760  0.04366737 14.7938 < 2.2e-16 ***
## DemHouseShareL2  0.05783309  0.05355049  1.0800   0.28075
## DemHouseShareL3  0.14499688  0.04787250  3.0288   0.00260 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4.0489
## Residual Sum of Squares: 1.3196
## R-Squared:      0.67408
## Adj. R-Squared: 0.64816
## F-statistic: 113.754 on 8 and 440 DF, p-value: < 2.22e-16
```

```r
AIC_adj(fe_m1_d)
```

```
## [1] -1433.895
```

```r
#model b (AR(1)) is best
```

Part f

The "b" specification with one lagged dependent variable (i.e. AR(1)) appears to fit best according to AIC.

```r
#M1 + region specific trends
fe_m2_a <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
summary(fe_m2_a)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails + Year * South + Year * Midwest +
##     Year * West, data = house_p, effect = "individual", model = "within")
##
## Balanced Panel: n = 28, T = 20, N = 560
##
## Residuals:
##        Min.     1st Qu.      Median     3rd Qu.        Max.
## -0.24169871 -0.03544019  0.00014272  0.03760914  0.32572908
##
## Coefficients:
##                    Estimate  Std. Error  t-value  Pr(>|t|)
## PartisanMidterm -0.01641309  0.00390553  -4.2025 3.104e-05 ***
## PresUnem         0.00060725  0.00146425   0.4147    0.6785
```

```
## GovUnem          0.00163122  0.00145572   1.1206    0.2630
## PresCoattails    0.02999270  0.00530655   5.6520 2.610e-08 ***
## GovCoattails     0.00623812  0.00668734   0.9328    0.3513
## Year             0.00066452  0.00049424   1.3445    0.1794
## Year:South      -0.01372969  0.00069453 -19.7682 < 2.2e-16 ***
## Year:Midwest    -0.00398070  0.00065198  -6.1056 1.998e-09 ***
## Year:West       -0.00066198  0.00065139  -1.0163    0.3100
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    5.2359
## Residual Sum of Squares: 2.0032
## R-Squared:      0.61741
## Adj. R-Squared: 0.59108
## F-statistic: 93.7781 on 9 and 523 DF, p-value: < 2.22e-16
```

```r
AIC_adj(fe_m2_a)
```

```
## [1] -1545.372
```

```r
fe_m2_b <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
summary(fe_m2_b)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails + Year * South + Year * Midwest +
##     Year * West + DemHouseShareL1, data = house_p, effect = "individual",
##     model = "within")
##
## Balanced Panel: n = 28, T = 19, N = 532
##
## Residuals:
##        Min.     1st Qu.      Median     3rd Qu.        Max.
## -0.21692571 -0.02768646  0.00070197  0.02993464  0.32095014
##
## Coefficients:
##                   Estimate  Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.02727637  0.00364154 -7.4903 3.189e-13 ***
## PresUnem        -0.00207291  0.00125092 -1.6571 0.0981321 .
## GovUnem          0.00108863  0.00124157  0.8768 0.3810113
## PresCoattails    0.01740954  0.00449187  3.8758 0.0001206 ***
## GovCoattails     0.00720545  0.00590462  1.2203 0.2229309
## Year             0.00060185  0.00045019  1.3369 0.1818846
## DemHouseShareL1  0.55760095  0.03814311 14.6187 < 2.2e-16 ***
## Year:South      -0.00617990  0.00082104 -7.5270 2.481e-13 ***
## Year:Midwest    -0.00179330  0.00060651 -2.9567 0.0032579 **
## Year:West        0.00024223  0.00058672  0.4128 0.6798973
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4.8065
## Residual Sum of Squares: 1.3048
## R-Squared:      0.72855
```

```
## Adj. R-Squared: 0.70822
## F-statistic: 132.583 on 10 and 494 DF, p-value: < 2.22e-16
```

```r
AIC_adj(fe_m2_b)
```

```
## [1] -1665.905
```

```r
fe_m2_c <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
summary(fe_m2_c)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
##     PresCoattails + GovCoattails + Year * South + Year * Midwest +
##     Year * West + DemHouseShareL1 + DemHouseShareL2, data = house_p,
##     effect = "individual", model = "within")
##
## Balanced Panel: n = 28, T = 18, N = 504
##
## Residuals:
##        Min.     1st Qu.      Median     3rd Qu.        Max.
## -0.20717643 -0.02631345  0.00087124  0.03119980  0.32302862
##
## Coefficients:
##                    Estimate  Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.02762300  0.00378335 -7.3012 1.245e-12 ***
## PresUnem        -0.00261753  0.00138376 -1.8916  0.059165 .
## GovUnem          0.00148033  0.00128039  1.1562  0.248210
## PresCoattails    0.02139730  0.00531883  4.0229 6.707e-05 ***
## GovCoattails     0.00724416  0.00602552  1.2022  0.229880
## Year             0.00072145  0.00050515  1.4282  0.153906
## DemHouseShareL1  0.52492684  0.04571049 11.4837 < 2.2e-16 ***
## DemHouseShareL2  0.03013501  0.04467089  0.6746  0.500265
## Year:South      -0.00632293  0.00094454 -6.6942 6.262e-11 ***
## Year:Midwest    -0.00186570  0.00067111 -2.7800  0.005656 **
## Year:West        0.00047969  0.00064496  0.7438  0.457400
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4.4732
## Residual Sum of Squares: 1.254
## R-Squared:      0.71965
## Adj. R-Squared: 0.69674
## F-statistic: 108.515 on 11 and 465 DF, p-value: < 2.22e-16
```

```r
AIC_adj(fe_m2_c)
```

```
## [1] -1567.798
```

```r
fe_m2_d <- plm(DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Yea
summary(fe_m2_d)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm(formula = DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem +
```

```
##     PresCoattails + GovCoattails + Year * South + Year * Midwest +
##     Year * West + DemHouseShareL1 + DemHouseShareL2 + DemHouseShareL3,
##     data = house_p, effect = "individual", model = "within")
##
## Balanced Panel: n = 28, T = 17, N = 476
##
## Residuals:
##        Min.     1st Qu.      Median     3rd Qu.        Max.
## -0.20735294 -0.02660910 -0.00084853  0.03064958  0.32200349
##
## Coefficients:
##                    Estimate  Std. Error t-value  Pr(>|t|)
## PartisanMidterm -0.02829859  0.00405122 -6.9852 1.069e-11 ***
## PresUnem        -0.00253884  0.00155951 -1.6280 0.1042536
## GovUnem          0.00134657  0.00151656  0.8879 0.3750777
## PresCoattails    0.02099371  0.00540707  3.8826 0.0001193 ***
## GovCoattails     0.00764972  0.00633665  1.2072 0.2280027
## Year             0.00065680  0.00054704  1.2006 0.2305447
## DemHouseShareL1  0.52080429  0.04704385 11.0706 < 2.2e-16 ***
## DemHouseShareL2  0.01127853  0.05159866  0.2186 0.8270780
## DemHouseShareL3  0.03569925  0.04905761  0.7277 0.4671875
## Year:South      -0.00625923  0.00109536 -5.7143 2.044e-08 ***
## Year:Midwest    -0.00172411  0.00074341 -2.3192 0.0208464 *
## Year:West        0.00059550  0.00070931  0.8395 0.4016240
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    4.0489
## Residual Sum of Squares: 1.1902
## R-Squared:      0.70605
## Adj. R-Squared: 0.67975
## F-statistic: 87.2695 on 12 and 436 DF, p-value: < 2.22e-16
```

```
AIC_adj(fe_m2_d)
```

```
## [1] -1475.033
```

```
#model b (AR(1)) is best
```

Part g

```
#Using each of four "best" models, forecast what will happen to
#the size of the Democratic majority in the average state in the 2019 and 2021
#sessions for the following single scenario. Assume the Democrats resume this
#state's governorship in 2019 and the presidency in 2021, and compute appropriate
#counterfactual values of PartisanMidterm, PresCoattails, GovCoattails. Assume
#unemployment falls to 3.6% for both elections and construct PresUnem and
#GovUnem accordingly. Set all trend variables at the average value they will take
#across regions in 2019 and 2021, respectively. Make appropriate assumptions for
#the prior value(s) of the outcome variable (e.g., the average Democratic House
#share in 2017).

#For each model, report or graph the predicted Democratic majority and its 95%
#confidence (or predictive) interval for the 2019 and 2021 sessions. Describe the
```

```
#substantive impact of your forecast results in as much detail as you feel comfortable,
#as well as how much confidence we should have in the forecasts. Be sure to
#consider the scale of the outcome variable in assessing what counts as a substantively
#large or small change.

#NB: As a check on your work, report the table of counterfactual covariate values
#you used to make your forecasts. Be very careful when constructing these values
#to capture to logic of the covariates; each one is tricky in its own way. To carry
#out the forecasts, use the simcf library's ldvsimev(), pay close attention to the
#example code, and think through all modifications you need to make.

house <- house %>%
  select(State, DemHouseShare, PartisanMidterm, PresUnem, GovUnem, PresCoattails,
         GovCoattails, Year, West, South, Midwest, DemHouseShareL1) %>%
  na.omit() %>%
  arrange(State, Year) %>%
  group_by(State) %>%
  mutate(YearXMidwest = Year* Midwest,
         YearXWest = Year * West,
         YearXSouth = Year * South)
house_p <- pdata.frame(house, index = "State")

#run candidate models (use PLM for all, making the RE models a Lagged DV equivalent)
fe_m1_b <- plm(DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails +
re_m1_b <- plm(DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails +
fe_m2_b <- plm(DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails +
re_m2_b <- plm(DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails +

# Extract model results from FE M1
pe.fe1_b <- coef(fe_m1_b)                                     # Point estimates of parameters
vc.fe1_b <- vcov(fe_m1_b)                                       # Var-cov matrix of point estimates
se.fe1_b <- sqrt(diag(vc.fe1_b))                                # std erros of point estimates
tstat.fe1_b <- abs(pe.fe1_b/se.fe1_b)                            # t-statistics
df.fe1_b <- rep(fe_m1_b$df.residual, length(tstat.fe1_b))  # residual degrees of freedom
pval.fe1_b <- 2*pt(tstat.fe1_b, df.fe1_b, lower.tail=FALSE)  # p-values
fe.fe1_b <- fixef(fe_m1_b)                                    # the (removed) fixed effects by group
resid.fe1_b <- resid(fe_m1_b)

# Extract model results from FE M2
pe.fe2_b <- coef(fe_m2_b)                                     # Point estimates of parameters
vc.fe2_b <- vcov(fe_m2_b)                                       # Var-cov matrix of point estimates
se.fe2_b <- sqrt(diag(vc.fe2_b))                                # std erros of point estimates
tstat.fe2_b <- abs(pe.fe2_b/se.fe2_b)                            # t-statistics
df.fe2_b <- rep(fe_m2_b$df.residual, length(tstat.fe2_b))  # residual degrees of freedom
pval.fe2_b <- 2*pt(tstat.fe2_b, df.fe2_b, lower.tail=FALSE)  # p-values
fe.fe2_b <- fixef(fe_m2_b)                                    # the (removed) fixed effects by group
resid.fe2_b <- resid(fe_m2_b)                                 # Residuals

# Extract model results from RE M1
pe.re1_b <- coef(re_m1_b)                                     # Point estimates of parameters
vc.re1_b <- vcov(re_m1_b)                                       # Var-cov matrix of point estimates
se.re1_b <- sqrt(diag(vc.re1_b))                                # std erros of point estimates
tstat.re1_b <- abs(pe.re1_b/se.re1_b)                            # t-statistics
```

```
df.re1_b <- rep(re_m1_b$df.residual, length(tstat.re1_b))  # residual degrees of freedom
pval.re1_b <- 2*pt(tstat.re1_b, df.re1_b, lower.tail=FALSE)  # p-values
re.re1_b <- random.effects(re_m1_b)                                    # the (removed) fixed efrects by gro
resid.re1_b <- resid(re_m1_b)

# Extract model results from RE M2
pe.re2_b <- coef(re_m2_b)                                # Point estimates of parameters
vc.re2_b <- vcov(re_m2_b)                                 # Var-cov matrix of point estimates
se.re2_b <- sqrt(diag(vc.re2_b))                          # std erros of point estimates
tstat.re2_b <- abs(pe.re2_b/se.re2_b)                      # t-statistics
df.re2_b <- rep(re_m2_b$df.residual, length(tstat.re2_b))  # residual degrees of freedom
pval.re2_b <- 2*pt(tstat.re2_b, df.re2_b, lower.tail=FALSE)  # p-values
re.re2_b <- random.effects(re_m2_b)                                    # the (removed) fixed efrects by gro
resid.re2_b <- resid(re_m2_b)                      # Residuals

#set number of simulates
sims <- 10000

# Interpret FE M1
simparam_fe1 <- MASS::mvrnorm(sims,pe.fe1_b,vc.fe1_b)
# Pull off the simulated lag coefficient
simphi_fe1 <- simparam_fe1[,ncol(simparam_fe1)]
# Put together the "constant" term (avg of the FEs, or a specific FE if you like)
# with the rest of the regressors
simbetas_fe1 <- cbind(rep(mean(fe.fe1_b), sims), simparam_fe1[,1:ncol(simparam_fe1)-1])

# Interpret FE M2
simparam_fe2 <- MASS::mvrnorm(sims,pe.fe2_b,vc.fe2_b)
# Pull off the simulated lag coefficient
simphi_fe2 <- simparam_fe2[,ncol(simparam_fe2)]
# Put together the "constant" term (avg of the FEs, or a specific FE if you like)
# with the rest of the regressors
simbetas_fe2 <- cbind(rep(mean(fe.fe2_b), sims), simparam_fe2[,1:ncol(simparam_fe2)-1])

# Interpret RE M1
simparam_re1 <- MASS::mvrnorm(sims,pe.re1_b,vc.re1_b)
# Pull off the simulated lag coefficient
simphi_re1 <- simparam_re1[,ncol(simparam_re1)]
# Put together the "constant" term
simbetas_re1 <- simparam_re1[,2:ncol(simparam_re1)-1]

# Interpret RE M2
simparam_re2 <- MASS::mvrnorm(sims,pe.re2_b,vc.re2_b)
# Pull off the simulated lag coefficient
simphi_re2 <- simparam_re2[,ncol(simparam_re2)]
# Put together the "constant" term
simbetas_re2 <- simparam_re2[,2:ncol(simparam_re2)-1]

# Formula for FE M1
formula_fe1 <- "DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails"
formula_fe1 <- as.formula(formula_fe1)

# Formula for FE M2
```

```
formula_fe2 <- "DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails + Ye
formula_fe2 <- as.formula(formula_fe2)

#Formula for RE M1
formula_re1 <- "DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails
formula_re1 <- as.formula(formula_re1)

#Formula for RE M2
formula_re2 <- "DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails + GovCoattails
formula_re2 <- as.formula(formula_re2)

#setup simcf xhyp objects
periods.out <- 2
xhyp_fe1 <- cfMake(formula_fe1, house_p, periods.out)
xhyp_fe2 <- cfMake(formula_fe2, house_p, periods.out)
xhyp_re1 <- cfMake(formula_re1, house_p, periods.out)
xhyp_re2 <- cfMake(formula_re2, house_p, periods.out)

#for each of the two forecast periods:
for(i in 1:periods.out){
  #FE M1
  xhyp_fe1 <- cfChange(xhyp_fe1, "Year", x=2019, xpre = 2017, scen=1)
  xhyp_fe1 <- cfChange(xhyp_fe1, "Year", x=2021, xpre = 2019, scen=2)

  xhyp_fe1 <- cfChange(xhyp_fe1, "PartisanMidterm", x = -1, xpre = 0, scen=1)
  xhyp_fe1 <- cfChange(xhyp_fe1, "PartisanMidterm", x = 0, xpre = -1, scen=2)

  xhyp_fe1 <- cfChange(xhyp_fe1, "PresUnem", x=-1*(3.6-5.97), scen=i)
  xhyp_fe1 <- cfChange(xhyp_fe1, "GovUnem", x=-1*(3.6-5.97), scen=1)
  xhyp_fe1 <- cfChange(xhyp_fe1, "GovUnem", x=1*(3.6-5.97), scen=2)

  xhyp_fe1 <- cfChange(xhyp_fe1, "GovCoattails", x=1, scen=1)
  xhyp_fe1 <- cfChange(xhyp_fe1, "PresCoattails", x=1, scen=2)

  #FE M2
  xhyp_fe2 <- cfChange(xhyp_fe2, "Year", x=2019, xpre = 2017, scen=1)
  xhyp_fe2 <- cfChange(xhyp_fe2, "Year", x=2021, xpre = 2019, scen=2)

  xhyp_fe2 <- cfChange(xhyp_fe2, "PartisanMidterm", x = -1, xpre = 0, scen=1)
  xhyp_fe2 <- cfChange(xhyp_fe2, "PartisanMidterm", x = 0, xpre = -1, scen=2)

  xhyp_fe2 <- cfChange(xhyp_fe2, "PresUnem", x=-1*(3.6-5.97), scen=i)
  xhyp_fe2 <- cfChange(xhyp_fe2, "GovUnem", x=-1*(3.6-5.97), scen=1)
  xhyp_fe2 <- cfChange(xhyp_fe2, "GovUnem", x=1*(3.6-5.97), scen=2)

  xhyp_fe2 <- cfChange(xhyp_fe2, "GovCoattails", x=1, scen=1)
  xhyp_fe2 <- cfChange(xhyp_fe2, "PresCoattails", x=1, scen=2)

  #RE M1
  xhyp_re1 <- cfChange(xhyp_re1, "Year", x=2019, xpre = 2017, scen=1)
  xhyp_re1 <- cfChange(xhyp_re1, "Year", x=2021, xpre = 2019, scen=2)

  xhyp_re1 <- cfChange(xhyp_re1, "PartisanMidterm", x = -1, xpre = 0, scen=1)
```

```r
  xhyp_re1 <- cfChange(xhyp_re1, "PartisanMidterm", x = 0, xpre = -1, scen=2)

  xhyp_re1 <- cfChange(xhyp_re1, "PresUnem", x=-1*(3.6-5.97), scen=i)
  xhyp_re1 <- cfChange(xhyp_re1, "GovUnem", x=-1*(3.6-5.97), scen=1)
  xhyp_re1 <- cfChange(xhyp_re1, "GovUnem", x=1*(3.6-5.97), scen=2)

  xhyp_re1 <- cfChange(xhyp_re1, "GovCoattails", x=1, scen=1)
  xhyp_re1 <- cfChange(xhyp_re1, "PresCoattails", x=1, scen=2)

  #RE M2
  xhyp_re2 <- cfChange(xhyp_re2, "Year", x=2019, xpre = 2017, scen=1)
  xhyp_re2 <- cfChange(xhyp_re2, "Year", x=2021, xpre = 2019, scen=2)

  xhyp_re2 <- cfChange(xhyp_re2, "PartisanMidterm", x = -1, xpre = 0, scen=1)
  xhyp_re2 <- cfChange(xhyp_re2, "PartisanMidterm", x = 0, xpre = -1, scen=2)

  xhyp_re2 <- cfChange(xhyp_re2, "PresUnem", x=-1*(3.6-5.97), scen=i)
  xhyp_re2 <- cfChange(xhyp_re2, "GovUnem", x=-1*(3.6-5.97), scen=1)
  xhyp_re2 <- cfChange(xhyp_re2, "GovUnem", x=1*(3.6-5.97), scen=2)

  xhyp_re2 <- cfChange(xhyp_re2, "GovCoattails", x=1, scen=1)
  xhyp_re2 <- cfChange(xhyp_re2, "PresCoattails", x=1, scen=2)
}

xhyp_fe1
```

```
## $x
##   DemHouseShare PartisanMidterm PresUnem GovUnem PresCoattails
## 1      0.526037              -1     2.37    2.37   -0.05263158
## 2      0.526037               0     2.37   -2.37    1.00000000
##   GovCoattails Year
## 1   1.00000000 2019
## 2  -0.01503759 2021
##
## $xpre
##   DemHouseShare PartisanMidterm   PresUnem   GovUnem PresCoattails
## 1      0.526037               0 -0.1416952 0.2155098   -0.05263158
## 2      0.526037              -1 -0.1416952 0.2155098   -0.05263158
##   GovCoattails Year
## 1  -0.01503759 2017
## 2  -0.01503759 2019
##
## $model
## DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +
##     GovCoattails
##
## attr(,"class")
## [1] "list"           "counterfactual"
```

```r
xhyp_fe2
```

```
## $x
##   DemHouseShare PartisanMidterm PresUnem GovUnem PresCoattails
## 1      0.526037              -1     2.37    2.37   -0.05263158
```

```
## 2      0.526037                0     2.37   -2.37    1.00000000
##   GovCoattails Year YearXMidwest YearXWest YearXSouth
## 1   1.00000000 2019     571.1429  571.1429   428.3571
## 2  -0.01503759 2021     571.1429  571.1429   428.3571
##
## $xpre
##   DemHouseShare PartisanMidterm   PresUnem   GovUnem PresCoattails
## 1      0.526037               0 -0.1416952 0.2155098   -0.05263158
## 2      0.526037              -1 -0.1416952 0.2155098   -0.05263158
##   GovCoattails Year YearXMidwest YearXWest YearXSouth
## 1  -0.01503759 2017     571.1429  571.1429   428.3571
## 2  -0.01503759 2019     571.1429  571.1429   428.3571
##
## $model
## DemHouseShare ~ PartisanMidterm + PresUnem + GovUnem + PresCoattails +
##     GovCoattails + Year + YearXMidwest + YearXWest + YearXSouth
##
## attr(,"class")
## [1] "list"           "counterfactual"
```

```
xhyp_re1
```

```
## $x
##   DemHouseShare PartisanMidterm PresUnem GovUnem PresCoattails
## 1      0.526037              -1     2.37    2.37   -0.05263158
## 2      0.526037               0     2.37   -2.37    1.00000000
##   GovCoattails Year
## 1   1.00000000 2019
## 2  -0.01503759 2021
##
## $xpre
##   DemHouseShare PartisanMidterm   PresUnem   GovUnem PresCoattails
## 1      0.526037               0 -0.1416952 0.2155098   -0.05263158
## 2      0.526037              -1 -0.1416952 0.2155098   -0.05263158
##   GovCoattails Year
## 1  -0.01503759 2017
## 2  -0.01503759 2019
##
## $model
## DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails +
##     GovCoattails
##
## attr(,"class")
## [1] "list"           "counterfactual"
```

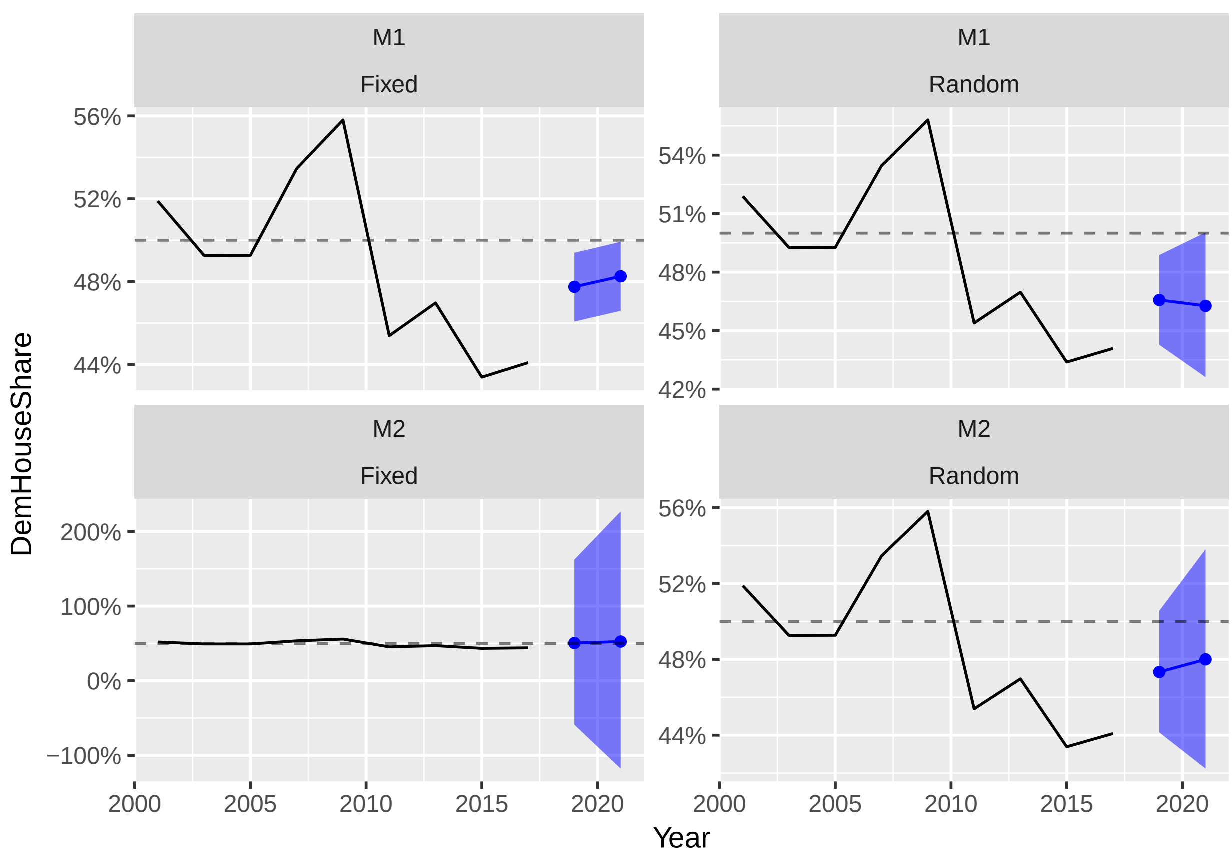
```
xhyp_re2
```

```
## $x
##   DemHouseShare PartisanMidterm PresUnem GovUnem PresCoattails
## 1      0.526037              -1     2.37    2.37   -0.05263158
## 2      0.526037               0     2.37   -2.37    1.00000000
##   GovCoattails Year   Midwest      West     South YearXMidwest YearXWest
## 1   1.00000000 2019 0.2857143 0.2857143 0.2142857     571.1429  571.1429
## 2  -0.01503759 2021 0.2857143 0.2857143 0.2142857     571.1429  571.1429
##   YearXSouth
## 1   428.3571
```

```
## 2   428.3571
##
## $xpre
##   DemHouseShare PartisanMidterm   PresUnem   GovUnem PresCoattails
## 1      0.526037               0 -0.1416952 0.2155098   -0.05263158
## 2      0.526037              -1 -0.1416952 0.2155098   -0.05263158
##   GovCoattails Year   Midwest      West     South YearXMidwest YearXWest
## 1  -0.01503759 2017 0.2857143 0.2857143 0.2142857     571.1429  571.1429
## 2  -0.01503759 2019 0.2857143 0.2857143 0.2142857     571.1429  571.1429
##   YearXSouth
## 1   428.3571
## 2   428.3571
##
## $model
## DemHouseShare ~ 1 + PartisanMidterm + PresUnem + GovUnem + PresCoattails +
##     GovCoattails + Year + Midwest + West + South + YearXMidwest +
##     YearXWest + YearXSouth
##
## attr(,"class")
## [1] "list"           "counterfactual"
```

```
#compute average phi for model spec
phi_fe1 <- mean(simphi_fe1)
phi_fe2 <- mean(simphi_fe2)
phi_re1 <- mean(simphi_re1)
phi_re2 <- mean(simphi_re2)

#compute mean of Y for 2017
lagY <- mean(house_p$DemHouseShareL1[house_p$Year == 2017])

#simulate expected values for each model spec
sim.fe1 <- ldvsimev(xhyp_fe1,               # The matrix of hypothetical x's
                    simbetas_fe1,           # The matrix of simulated betas
                    ci=0.95,            # Desired confidence interval
                    phi=phi_fe1,            # estimated AR parameters; length must match lagY
                    lagY=lagY)  # lags of y, most recent last

sim.fe2 <- ldvsimev(xhyp_fe2,               # The matrix of hypothetical x's
                    simbetas_fe2,           # The matrix of simulated betas
                    ci=0.95,            # Desired confidence interval
                    phi=phi_fe2,            # estimated AR parameters; length must match lagY
                    lagY=lagY)  # lags of y, most recent last

sim.re1 <- ldvsimev(xhyp_re1,               # The matrix of hypothetical x's
                    simbetas_re1,           # The matrix of simulated betas
                    ci=0.95,            # Desired confidence interval
                    phi=phi_re1,            # estimated AR parameters; length must match lagY
                    lagY=lagY)  # lags of y, most recent last

sim.re2 <- ldvsimev(xhyp_re2,               # The matrix of hypothetical x's
                    simbetas_re2,           # The matrix of simulated betas
                    ci=0.95,            # Desired confidence interval
                    phi=phi_re2,            # estimated AR parameters; length must match lagY
                    lagY=lagY)  # lags of y, most recent last
```

```r
#compile results as tidy df
simmed <- data.frame("FEvsRE" = c(rep("Fixed", 4), rep("Random", 4)),
                     "Spec" = rep(c("M1", "M1", "M2", "M2"), 2),
                      "Year" = rep(c(2019, 2021), 4),
                     "DemHouseShare" = c(sim.fe1$pe, sim.fe2$pe, sim.re1$pe, sim.re2$pe),
                     "lower" = c(sim.fe1$lower, sim.fe2$lower, sim.re1$lower, sim.re2$lower),
                     "upper" = c(sim.fe1$upper, sim.fe2$upper, sim.re1$upper, sim.re2$upper),
                     "se" = c(sim.fe1$se, sim.fe2$se, sim.re1$se, sim.re2$se))

#compute average state's ts
house_avg <- house_p %>%
  filter(Year >= 2000) %>%
  group_by(Year) %>%
  summarize(DemHouseShare = mean(DemHouseShare))

ggplot(simmed, aes(x = Year, y = DemHouseShare, ymax = upper, ymin = lower)) +
  facet_wrap(Spec ~ FEvsRE, scales = "free_y") +
  geom_point(color = "blue") +
  geom_line(color = "blue") +
  geom_ribbon(alpha = .5, color = NA, fill = "blue") +
  geom_line(data=house_avg, aes(ymin = NULL, ymax = NULL)) +
  geom_abline(intercept = .50, slope = 0, linetype = 2, alpha = .5) +
  scale_y_continuous(labels = scales::percent)
```



Part h

NB: Y scales vary between facets in plot, otherwise it's hard to show FE M2's gigantic uncertainty while also showing the other three meaningfully.

Though its forecast is the most uncertain, I think that the fixed effects M2 specification is what I would choose for my final model even if it's . The evidence from checking the stationarity of the series suggests that the between-State variation in DemHouseShare levels and in autocorrelation is considerable. Without attempting to model individual intercepts and trends, there's a greater threat that the temporal autocorrelation will bias model estimates. All models predict pretty consistent effects for Coattails and Partisan midterm in terms of sign, but there are real differences in what the models predict substantively as far as the Democrats retaking the average House majority is concerned. The conclusions of the FE M2 model are that there indeed are some effects of presidential coattails and partisan midterm corrections (on average, we expect that 2019 and 2021 will see Democratic gains). However, compared to state differences in levels and dynamics of state legislature composition, the average effects of these two theoretical perspectives is pretty weak and so the forecasts have very wide 95% prediction intervals. So while within-States we expect that the partisan midterm boost and that there will be a Democratic wave in 2021, we really have no idea what the average level will be. I don't have it worked out in any formal way, but this seems akin to what we get with ARIMA models, where we can really only talk about what leads to differences and not levels given then non-stationarity of the series, despite not integrating the panel in the present case.

```
#Using everything you have learned in this assignment and in the
#course, which of the four best models should we use to write-up our results,
#and why? (You may argue for multiple models if you think that's appropriate.)
#What are your final substantive conclusions? Substantively, does it make much
#difference which model we choose? How does this affect the way you would
#write this analysis up in a paper?
```