Time Series Forecasting Model

Elizabeth Goodwin

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Contents

Disclaimer: Sorry, it spits out a lot more info than needed. Couldn't figure out how to get it to not do that in time so I just included it so it still had all the needed info.

1 Loading Dataset

Loaded a CSV file of the dataset

```
prison <- read_csv('prison.csv')
```

```
## New names:
## * ‘‘ -> ...1

## Rows: 49 Columns: 6

## -- Column specification ------------------------------------------------------
## Delimiter: ","
## dbl (6): ...1, PRISONPC, MURDERPC, RAPEPC, ROBPC, ASSAULPC
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
colnames(prison)[1] = 'year'
```

2 Log and Differencing

In the below code block, I took the log of the various variables and took first differences. I also renamed the variables to something more understandable

```
prison <- prison %>% mutate (
  prisoners = log(PRISONPC),
  murders = log(MURDERPC),
  rapes = log(RAPEPC),
  robberies = log(ROBPC),
  assaults = log(ASSAULPC)
) %>% select(year, prisoners, murders, rapes, robberies, assaults) %>% mutate(
  prisoners = difference(prisoners),
  murders = difference(murders),
  rapes = difference(rapes),
  robberies = difference(robberies),
  assaults = difference(assaults)
) %>% filter(year > 1948)
```

Converted the dataset into format used by time series package.

```
prisoners <- ts(prison$prisoners, start = 1949, frequency = 1) %>% na.remove()
murders <- ts(prison$murders, start = 1949, frequency = 1)%>% na.remove()
rapes <- ts(prison$rapes, start = 1949, frequency = 1)%>% na.remove()
robberies <- ts(prison$robberies, start = 1949, frequency = 1)%>% na.remove()
assaults <- ts(prison$assaults, start = 1949, frequency = 1) %>% na.remove()
v1 <- cbind(prisoners, murders, rapes, robberies, assaults) %>% na.remove()
colnames(v1) <- cbind("prisoners", "murders", "rapes", "robberies", "assaults")
```

```
autoplot(prisoners, ylab = 'prisoners')
```

```
autoplot(murders, ylab='murders')
```

```
autoplot(rapes, ylab = 'rapes')
```

```
autoplot(robberies, ylab = 'robberies')
```

```
autoplot(assaults, ylab = 'assaults')
```

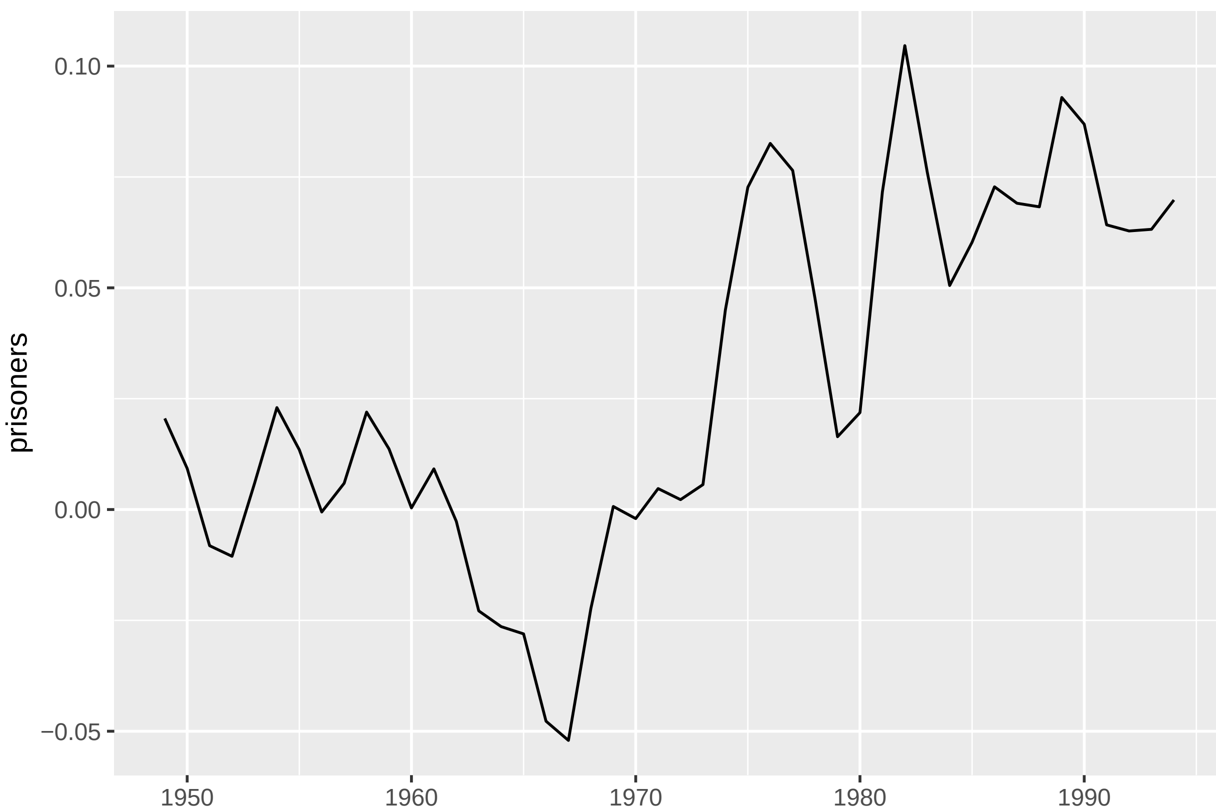

Figure 1: Plots of the raw data

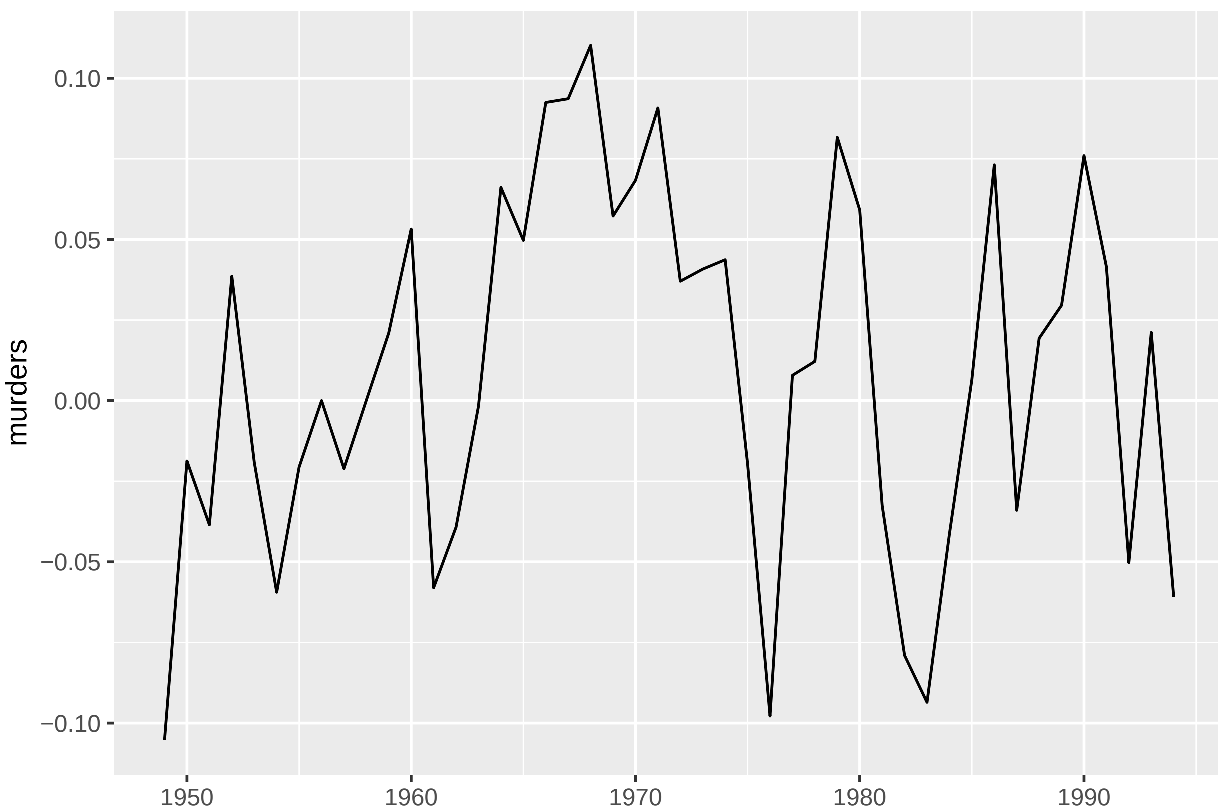

Figure 2: Plots of the raw data

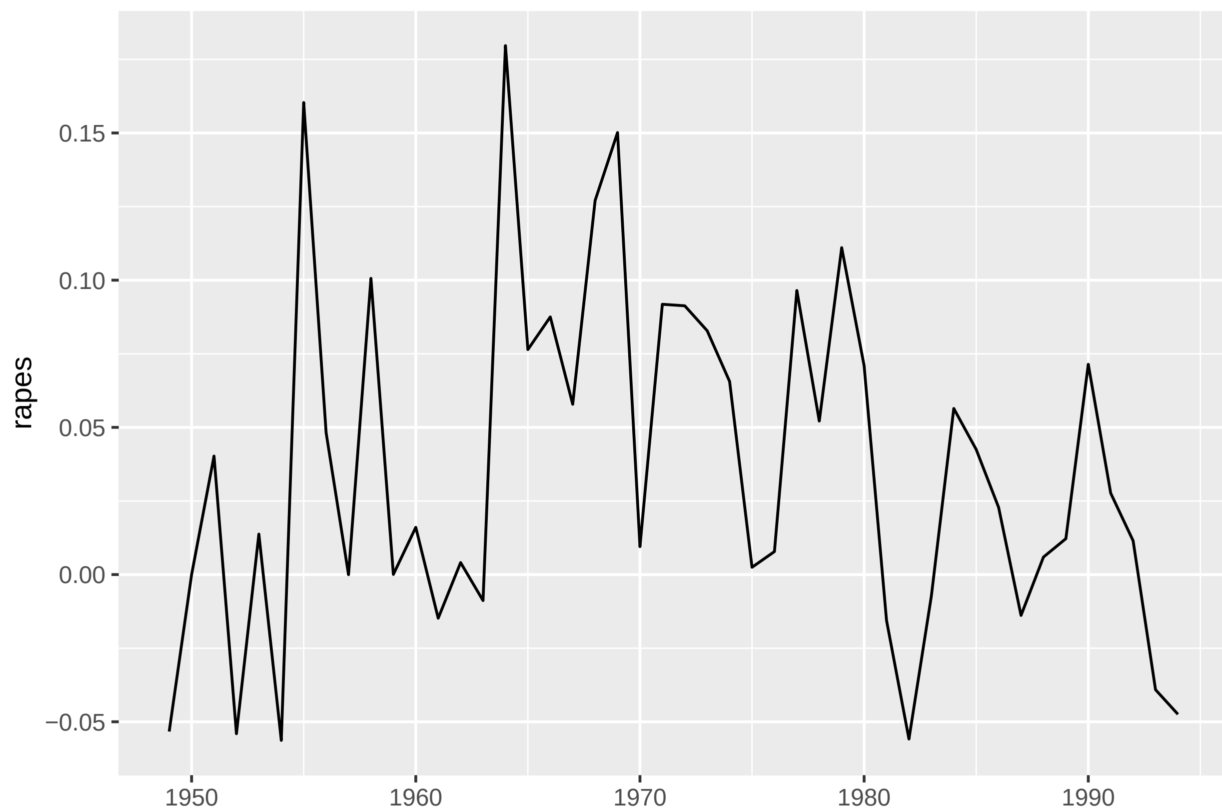

Figure 3: Plots of the raw data

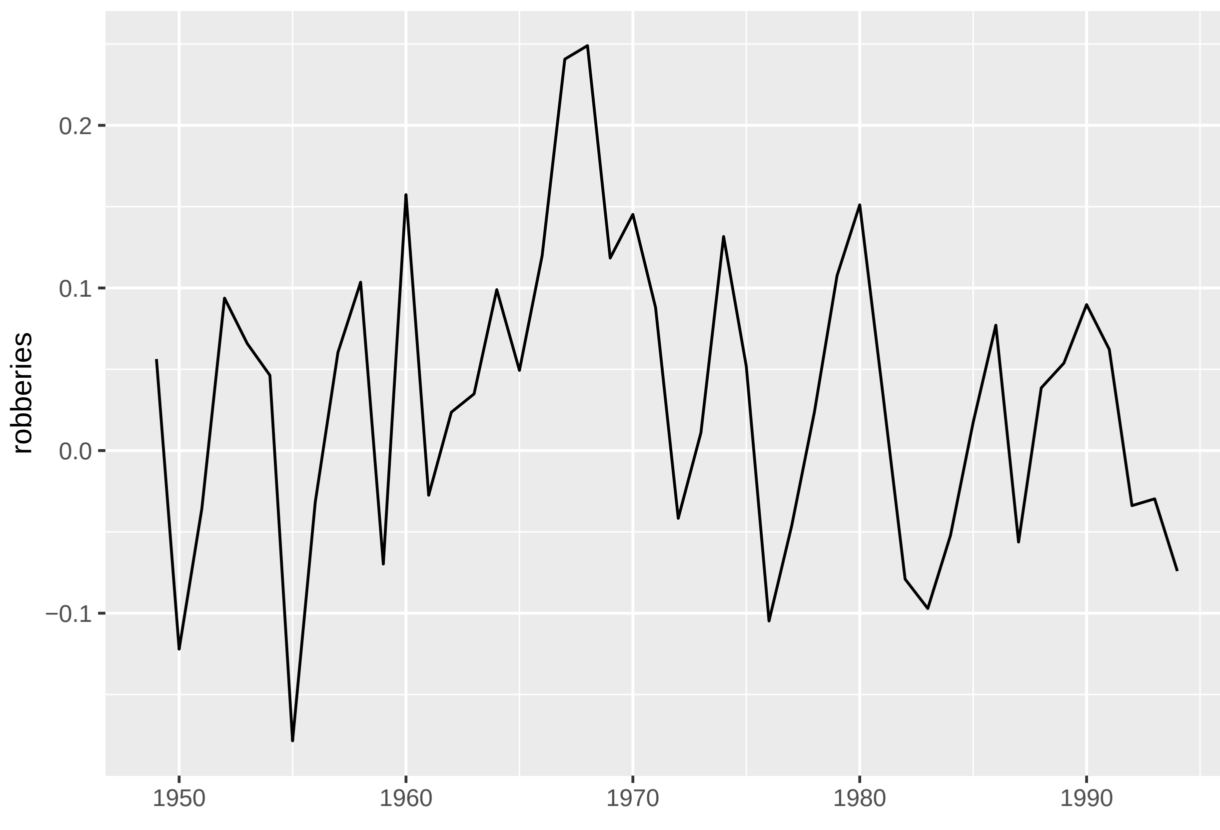

Figure 4: Plots of the raw data

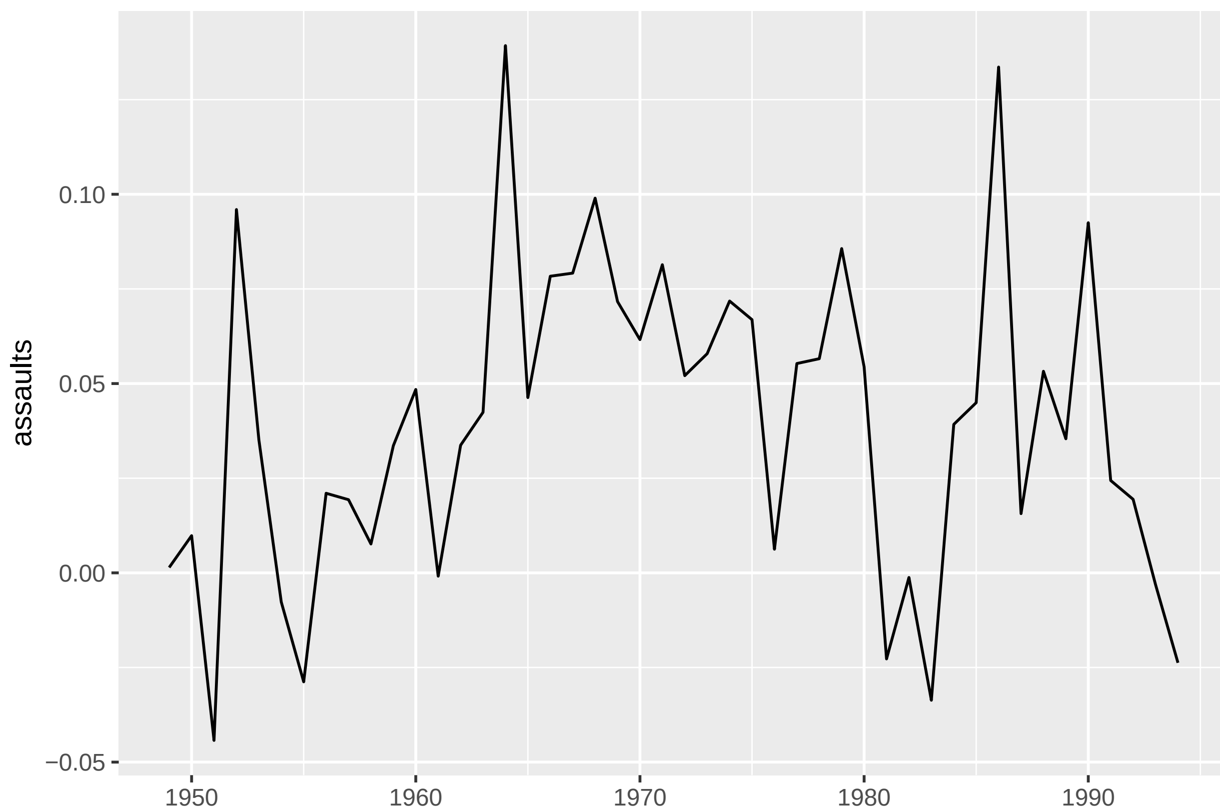

Figure 5: Plots of the raw data

3 Model Creation

Lag selection. Uses various methods to try and determine the optimal lag for the model

```
lagselect <- VARselect(v1, lag.max = 15, type = "const")
lagselect$selection
```

```
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      6      6      6      7
```

3.1 Model

```
summary(Model1)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: prisoners, murders, rapes, robberies, assaults
## Deterministic variables: const
## Sample size: 44
## Log Likelihood: 458.923
## Roots of the characteristic polynomial:
## 0.8153 0.6588 0.6588 0.5953 0.5953 0.475 0.4544 0.338 0.338 0.1181
## Call:
## VAR(y = v1, p = 2, type = "const", exogen = NULL)
##
##
## Estimation results for equation prisoners:
## ==========================================
## prisoners = prisoners.l1 + murders.l1 + rapes.l1 + robberies.l1 + assaults.l1 + prisoners.l2 + murde
##
##                Estimate Std. Error t value Pr(>|t|)
## prisoners.l1  1.336898   0.166352   8.037 2.84e-09 ***
## murders.l1    0.057699   0.104593   0.552   0.5849
## rapes.l1     -0.026918   0.056121  -0.480   0.6346
## robberies.l1  0.046776   0.051844   0.902   0.3735
## assaults.l1  -0.052454   0.102181  -0.513   0.6111
## prisoners.l2 -0.428590   0.184568  -2.322   0.0265 *
## murders.l2    0.147084   0.104332   1.410   0.1680
## rapes.l2     -0.017007   0.059704  -0.285   0.7775
## robberies.l2 -0.101370   0.046048  -2.201   0.0348 *
## assaults.l2  -0.011966   0.105087  -0.114   0.9100
## const         0.007750   0.006672   1.162   0.2538
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.01628 on 33 degrees of freedom
## Multiple R-Squared: 0.8788,  Adjusted R-squared: 0.842
## F-statistic: 23.92 on 10 and 33 DF,  p-value: 2.518e-12
##
```

```
##
## Estimation results for equation murders:
## ========================================
## murders = prisoners.l1 + murders.l1 + rapes.l1 + robberies.l1 + assaults.l1 + prisoners.l2 + murders
##
##              Estimate Std. Error t value Pr(>|t|)
## prisoners.l1 -0.97997    0.46603  -2.103   0.0432 *
## murders.l1    0.11582    0.29302   0.395   0.6952
## rapes.l1      0.24674    0.15722   1.569   0.1261
## robberies.l1  0.03132    0.14524   0.216   0.8306
## assaults.l1   0.05311    0.28626   0.186   0.8540
## prisoners.l2  0.77599    0.51706   1.501   0.1429
## murders.l2   -0.28616    0.29228  -0.979   0.3347
## rapes.l2      0.24385    0.16726   1.458   0.1543
## robberies.l2  0.05617    0.12900   0.435   0.6661
## assaults.l2   0.32893    0.29440   1.117   0.2719
## const        -0.01867    0.01869  -0.999   0.3252
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.04561 on 33 degrees of freedom
## Multiple R-Squared: 0.4602,  Adjusted R-squared: 0.2966
## F-statistic: 2.813 on 10 and 33 DF,  p-value: 0.01224
##
##
## Estimation results for equation rapes:
## ======================================
## rapes = prisoners.l1 + murders.l1 + rapes.l1 + robberies.l1 + assaults.l1 + prisoners.l2 + murders.l2
##
##                Estimate Std. Error t value Pr(>|t|)
## prisoners.l1 -1.074e+00  5.736e-01  -1.873   0.0700 .
## murders.l1   -2.574e-01  3.607e-01  -0.714   0.4805
## rapes.l1      6.472e-02  1.935e-01   0.334   0.7402
## robberies.l1  1.459e-01  1.788e-01   0.816   0.4204
## assaults.l1   3.118e-01  3.524e-01   0.885   0.3827
## prisoners.l2  7.631e-01  6.365e-01   1.199   0.2391
## murders.l2   -7.246e-01  3.598e-01  -2.014   0.0522 .
## rapes.l2      2.102e-01  2.059e-01   1.021   0.3147
## robberies.l2  2.536e-01  1.588e-01   1.597   0.1197
## assaults.l2   4.762e-01  3.624e-01   1.314   0.1979
## const        -1.766e-06  2.301e-02   0.000   0.9999
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.05614 on 33 degrees of freedom
## Multiple R-Squared: 0.2914,  Adjusted R-squared: 0.0767
## F-statistic: 1.357 on 10 and 33 DF,  p-value: 0.2428
##
##
## Estimation results for equation robberies:
## ==========================================
## robberies = prisoners.l1 + murders.l1 + rapes.l1 + robberies.l1 + assaults.l1 + prisoners.l2 + murde
```

```
##
##               Estimate Std. Error t value Pr(>|t|)
## prisoners.l1 -1.669655   0.733346  -2.277   0.0294 *
## murders.l1    0.235012   0.461091   0.510   0.6137
## rapes.l1      0.107568   0.247405   0.435   0.6665
## robberies.l1  0.007798   0.228548   0.034   0.9730
## assaults.l1   0.219263   0.450455   0.487   0.6296
## prisoners.l2  0.945641   0.813651   1.162   0.2535
## murders.l2    0.176841   0.459938   0.384   0.7031
## rapes.l2      0.324963   0.263199   1.235   0.2257
## robberies.l2 -0.150971   0.203000  -0.744   0.4623
## assaults.l2   0.109537   0.463266   0.236   0.8145
## const         0.026723   0.029414   0.909   0.3702
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.07177 on 33 degrees of freedom
## Multiple R-Squared: 0.5156,  Adjusted R-squared: 0.3688
## F-statistic: 3.512 on 10 and 33 DF,  p-value: 0.00305
##
##
## Estimation results for equation assaults:
## =========================================
## assaults = prisoners.l1 + murders.l1 + rapes.l1 + robberies.l1 + assaults.l1 + prisoners.l2 + murders
##
##              Estimate Std. Error t value Pr(>|t|)
## prisoners.l1 -0.39019    0.41591  -0.938    0.355
## murders.l1   -0.08015    0.26150  -0.307    0.761
## rapes.l1      0.15705    0.14031   1.119    0.271
## robberies.l1  0.04641    0.12962   0.358    0.723
## assaults.l1   0.10785    0.25547   0.422    0.676
## prisoners.l2  0.22339    0.46145   0.484    0.632
## murders.l2   -0.17900    0.26085  -0.686    0.497
## rapes.l2      0.15335    0.14927   1.027    0.312
## robberies.l2 -0.10442    0.11513  -0.907    0.371
## assaults.l2   0.40660    0.26274   1.548    0.131
## const         0.01703    0.01668   1.021    0.315
##
##
## Residual standard error: 0.0407 on 33 degrees of freedom
## Multiple R-Squared: 0.2862,  Adjusted R-squared: 0.0699
## F-statistic: 1.323 on 10 and 33 DF,  p-value: 0.2592
##
##
##
## Covariance matrix of residuals:
##            prisoners    murders      rapes robberies   assaults
## prisoners  2.650e-04 -0.0001495 -0.0001191 5.147e-05 -8.364e-05
## murders   -1.495e-04  0.0020801  0.0011714 2.007e-03  1.384e-03
## rapes     -1.191e-04  0.0011714  0.0031517 2.606e-04  8.475e-04
## robberies  5.147e-05  0.0020071  0.0002606 5.151e-03  1.661e-03
## assaults  -8.364e-05  0.0013842  0.0008475 1.661e-03  1.657e-03
##
```

```
## Correlation matrix of residuals:
##            prisoners murders    rapes robberies assaults
## prisoners   1.00000 -0.2014 -0.13028   0.04405  -0.1262
## murders    -0.20139  1.0000  0.45749   0.61317   0.7456
## rapes      -0.13028  0.4575  1.00000   0.06469   0.3709
## robberies   0.04405  0.6132  0.06469   1.00000   0.5686
## assaults   -0.12622  0.7456  0.37089   0.56857   1.0000
```

4 Results

4.1 Impulse response function

The following impulse response functions. I then rotated the various impulse response functions, which are shown in Figures 6 through 10. An exogenous increase in prison does cause a decrease in crime, at least cumulatively. This conclusion does not depend on order of variables.

```
irf_original_order <- irf(Model1, impulse ="prisoners", response = c('prisoners', 'murders', 'rapes', 'r
```

```
plot(irf_original_order)
```

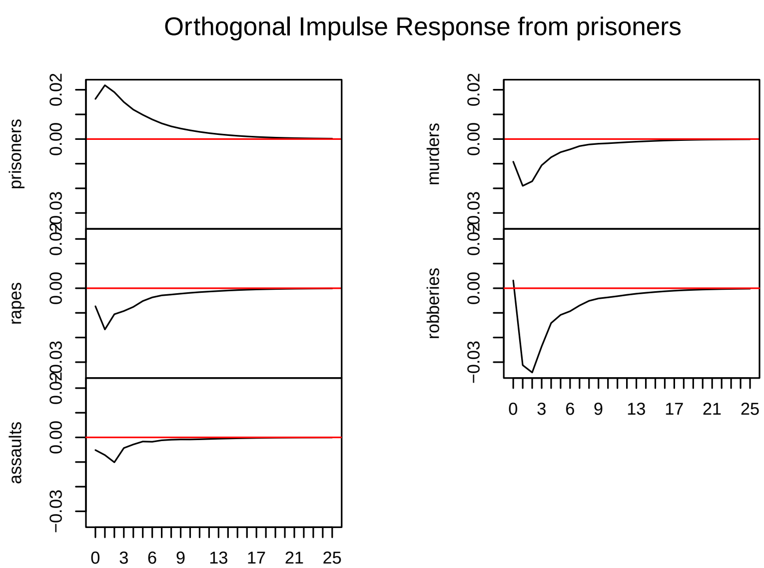

Figure 6: Original Order non-cumulative

```
res = c('murders', 'rapes', 'robberies', 'assaults', 'prisoners')
irf_2 <- irf(Model1, impulse ="prisoners", response = res, n.ahead = 25, ortho = T , runs = 100)
```

```
plot(irf_2)
```

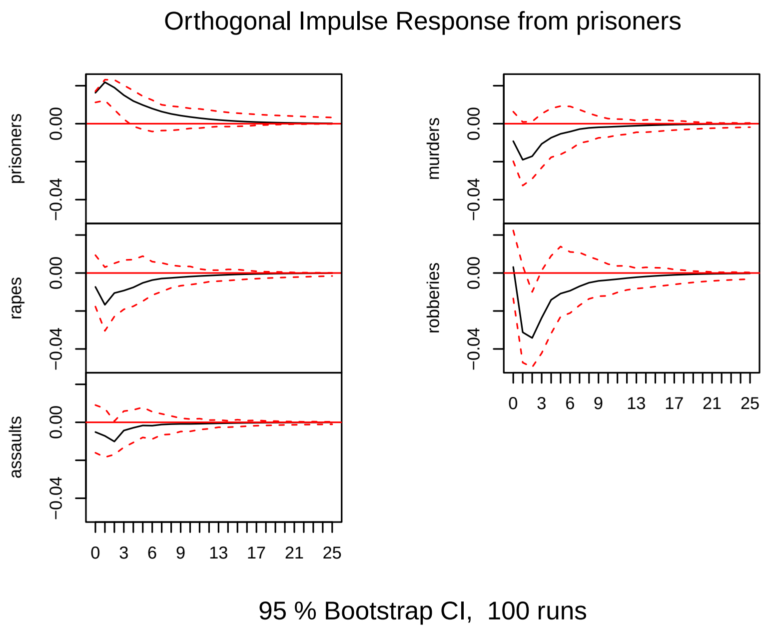

Figure 7: Murder first non-cumulative

```
res = c('rapes', 'robberies', 'assaults', 'prisoners','murders')
irf_3 <- irf(Model1, impulse ="prisoners", response = res, n.ahead = 25, ortho = T , runs = 100)
```

```
plot(irf_3)
```

```
res = c('robberies', 'assaults', 'prisoners', 'murders', 'rapes' )
irf_4 <- irf(Model1, impulse ="prisoners", response = res, n.ahead = 25, ortho = T , runs = 100)
```

```
plot(irf_4)
```

```
res = c( 'assaults', 'prisoners', 'murders', 'rapes', 'robberies' )
irf_5 <- irf(Model1, impulse ="prisoners", response = res, n.ahead = 25, ortho = T , runs = 100)
```

```
plot(irf_5)
```

4.2 Variance decomposition:

Variance decomposition. Both original output and graphs included. Graphs in Figure 11

```
vardecomp <- fevd(Model1, n.ahead = 25)
vardecomp
```

```
## $prisoners
```

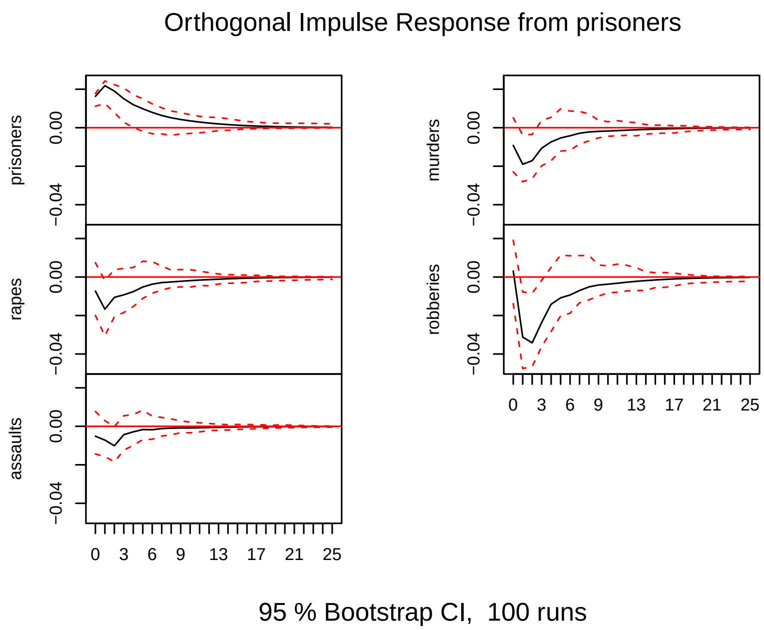

Figure 8: Rapes first non-cumulative

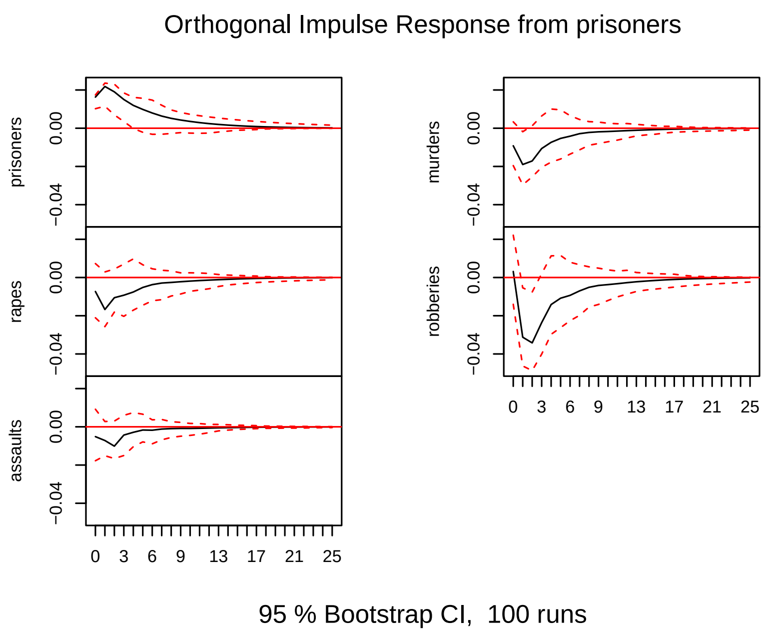

Figure 9: Robberies first non-cumulative

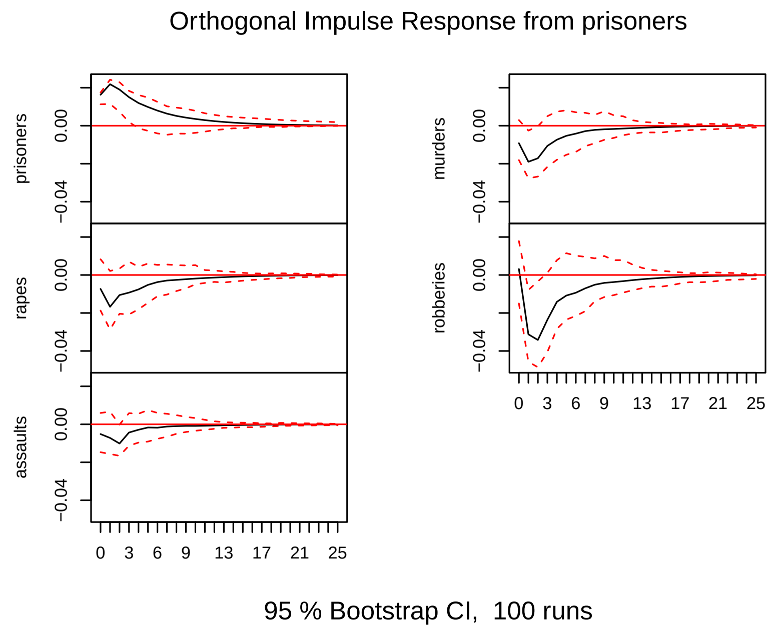

Figure 10: Assaults first non-cumulative

```
##       prisoners     murders       rapes   robberies    assaults
##  [1,] 1.0000000 0.000000000 0.000000000 0.000000000 0.000000000
##  [2,] 0.9770575 0.008057548 0.006408708 0.005971148 0.002505121
##  [3,] 0.9436579 0.033827140 0.006266856 0.010565189 0.005682964
##  [4,] 0.8933239 0.064452159 0.006033729 0.025957421 0.010232797
##  [5,] 0.8647279 0.087284759 0.008405801 0.029116729 0.010464774
##  [6,] 0.8513902 0.100895038 0.010642413 0.027402562 0.009669826
##  [7,] 0.8429058 0.108971517 0.012428780 0.026138929 0.009555021
##  [8,] 0.8369224 0.113759380 0.014052403 0.025459500 0.009806294
##  [9,] 0.8331248 0.116357970 0.015270509 0.025080366 0.010166333
## [10,] 0.8310531 0.117627541 0.015984684 0.024815130 0.010519585
## [11,] 0.8299691 0.118248398 0.016356543 0.024646801 0.010779112
## [12,] 0.8293670 0.118588115 0.016559023 0.024562887 0.010922972
## [13,] 0.8290086 0.118795423 0.016676197 0.024528868 0.010990885
## [14,] 0.8287921 0.118929813 0.016744273 0.024511700 0.011022131
## [15,] 0.8286563 0.119021992 0.016784484 0.024500172 0.011037022
## [16,] 0.8285644 0.119088412 0.016810181 0.024492750 0.011044249
## [17,] 0.8284992 0.119136785 0.016827942 0.024487993 0.011048038
## [18,] 0.8284534 0.119171202 0.016840501 0.024484453 0.011050460
## [19,] 0.8284218 0.119194977 0.016849284 0.024481651 0.011052303
## [20,] 0.8284003 0.119211059 0.016855359 0.024479570 0.011053757
## [21,] 0.8283857 0.119221782 0.016859530 0.024478128 0.011054866
## [22,] 0.8283760 0.119228848 0.016862359 0.024477156 0.011055680
## [23,] 0.8283695 0.119233469 0.016864246 0.024476505 0.011056258
## [24,] 0.8283653 0.119236485 0.016865492 0.024476074 0.011056654
## [25,] 0.8283625 0.119238462 0.016866311 0.024475794 0.011056918
##
## $murders
##       prisoners   murders      rapes   robberies     assaults
```

```
##  [1,] 0.0405589 0.9594411 0.00000000 0.000000000 0.0000000000
##  [2,] 0.1594917 0.7880765 0.05031412 0.001418782 0.0006989799
##  [3,] 0.2059666 0.6281666 0.11108230 0.010540399 0.0442441134
##  [4,] 0.2147796 0.5696711 0.10676603 0.042515440 0.0662678642
##  [5,] 0.2158481 0.5449138 0.10142950 0.051912671 0.0858958789
##  [6,] 0.2187573 0.5421626 0.09972720 0.051333829 0.0880190573
##  [7,] 0.2206579 0.5415864 0.09900587 0.051087405 0.0876623911
##  [8,] 0.2212890 0.5416026 0.09905645 0.050869192 0.0871827387
##  [9,] 0.2216192 0.5412811 0.09940013 0.050706280 0.0869933172
## [10,] 0.2219482 0.5407646 0.09959675 0.050624459 0.0870660814
## [11,] 0.2223217 0.5402827 0.09964225 0.050578579 0.0871748183
## [12,] 0.2226476 0.5399471 0.09963368 0.050536864 0.0872348412
## [13,] 0.2229014 0.5397259 0.09961542 0.050515910 0.0872413595
## [14,] 0.2230883 0.5395782 0.09959591 0.050507658 0.0872299827
## [15,] 0.2232218 0.5394800 0.09957935 0.050502753 0.0872160814
## [16,] 0.2233118 0.5394165 0.09956731 0.050499804 0.0872045774
## [17,] 0.2233698 0.5393765 0.09955943 0.050498048 0.0871961785
## [18,] 0.2234067 0.5393516 0.09955457 0.050496619 0.0871904814
## [19,] 0.2234305 0.5393358 0.09955163 0.050495305 0.0871867713
## [20,] 0.2234458 0.5393257 0.09954985 0.050494251 0.0871844174
## [21,] 0.2234557 0.5393190 0.09954878 0.050493498 0.0871829409
## [22,] 0.2234623 0.5393146 0.09954812 0.050492985 0.0871820167
## [23,] 0.2234666 0.5393116 0.09954769 0.050492639 0.0871814341
## [24,] 0.2234695 0.5393096 0.09954740 0.050492410 0.0871810601
## [25,] 0.2234715 0.5393083 0.09954721 0.050492261 0.0871808140
##
## $rapes
##        prisoners   murders     rapes  robberies   assaults
##  [1,] 0.01697346 0.1938407 0.7891858 0.00000000 0.00000000
##  [2,] 0.09189163 0.1784185 0.6853641 0.02580669 0.01851904
##  [3,] 0.10283946 0.1512410 0.5949451 0.07700484 0.07396964
##  [4,] 0.11752022 0.1495267 0.5700560 0.07891419 0.08398287
##  [5,] 0.12706141 0.1520965 0.5564225 0.07699052 0.08742915
##  [6,] 0.13128118 0.1559586 0.5498731 0.07605078 0.08683629
##  [7,] 0.13316670 0.1588542 0.5463104 0.07546278 0.08620589
##  [8,] 0.13428869 0.1602435 0.5444645 0.07510571 0.08589759
##  [9,] 0.13525717 0.1606841 0.5432187 0.07494674 0.08589328
## [10,] 0.13601265 0.1607906 0.5423792 0.07482252 0.08599512
## [11,] 0.13658444 0.1608024 0.5418447 0.07473279 0.08603564
## [12,] 0.13700670 0.1607872 0.5414855 0.07468311 0.08603751
## [13,] 0.13732055 0.1607680 0.5412358 0.07465304 0.08602263
## [14,] 0.13754202 0.1607553 0.5410631 0.07463482 0.08600481
## [15,] 0.13769052 0.1607500 0.5409459 0.07462450 0.08598905
## [16,] 0.13778736 0.1607496 0.5408676 0.07461811 0.08597735
## [17,] 0.13785042 0.1607512 0.5408158 0.07461330 0.08596934
## [18,] 0.13789143 0.1607532 0.5407816 0.07460966 0.08596410
## [19,] 0.13791806 0.1607551 0.5407591 0.07460706 0.08596072
## [20,] 0.13793538 0.1607564 0.5407444 0.07460528 0.08595858
## [21,] 0.13794677 0.1607573 0.5407346 0.07460407 0.08595722
## [22,] 0.13795432 0.1607578 0.5407282 0.07460325 0.08595637
## [23,] 0.13795936 0.1607582 0.5407240 0.07460270 0.08595582
## [24,] 0.13796273 0.1607583 0.5407211 0.07460235 0.08595545
## [25,] 0.13796498 0.1607584 0.5407192 0.07460211 0.08595521
##
```

```
## $robberies
##        prisoners   murders      rapes robberies    assaults
##  [1,] 0.001940416 0.4032928 0.05543973 0.5393270 0.000000000
##  [2,] 0.149365083 0.3760105 0.04794606 0.4216360 0.005042336
##  [3,] 0.244609406 0.3024830 0.11944038 0.3240326 0.009434566
##  [4,] 0.276839536 0.2728668 0.11844190 0.3080799 0.023771881
##  [5,] 0.273877308 0.2609697 0.10930180 0.3126233 0.043227889
##  [6,] 0.276994868 0.2623516 0.10678763 0.3067486 0.047117279
##  [7,] 0.280927919 0.2639426 0.10554270 0.3027953 0.046791464
##  [8,] 0.282885073 0.2652172 0.10507858 0.3003887 0.046430452
##  [9,] 0.283680535 0.2660323 0.10523546 0.2987630 0.046288742
## [10,] 0.284237604 0.2662409 0.10545032 0.2977401 0.046331054
## [11,] 0.284831868 0.2661289 0.10548288 0.2970962 0.046460122
## [12,] 0.285348794 0.2659746 0.10543994 0.2966790 0.046557591
## [13,] 0.285731907 0.2658633 0.10539867 0.2964191 0.046587059
## [14,] 0.286001117 0.2657876 0.10536573 0.2962594 0.046586142
## [15,] 0.286193201 0.2657365 0.10533892 0.2961529 0.046578480
## [16,] 0.286325671 0.2657043 0.10531869 0.2960805 0.046570882
## [17,] 0.286412161 0.2656857 0.10530507 0.2960324 0.046564675
## [18,] 0.286467251 0.2656755 0.10529652 0.2960005 0.046560198
## [19,] 0.286502735 0.2656698 0.10529124 0.2959789 0.046557264
## [20,] 0.286525880 0.2656664 0.10528792 0.2959643 0.046555459
## [21,] 0.286541002 0.2656642 0.10528583 0.2959546 0.046554372
## [22,] 0.286550907 0.2656628 0.10528452 0.2959481 0.046553715
## [23,] 0.286557462 0.2656618 0.10528367 0.2959438 0.046553314
## [24,] 0.286561842 0.2656611 0.10528310 0.2959409 0.046553065
## [25,] 0.286564778 0.2656606 0.10528272 0.2959390 0.046552905
##
## $assaults
##        prisoners   murders       rapes  robberies  assaults
##  [1,] 0.01593143 0.5406205 0.001195931 0.02466483 0.4175874
##  [2,] 0.04300762 0.5125141 0.029737465 0.02801269 0.3867281
##  [3,] 0.08110671 0.4234287 0.079894658 0.02454370 0.3910262
##  [4,] 0.08592565 0.4105708 0.081010373 0.03495633 0.3875368
##  [5,] 0.08617172 0.4030077 0.078012480 0.03966724 0.3931409
##  [6,] 0.08659965 0.4052368 0.077884275 0.03935856 0.3909207
##  [7,] 0.08740426 0.4056343 0.077886547 0.04031003 0.3887648
##  [8,] 0.08770422 0.4058472 0.078073016 0.04052548 0.3878500
##  [9,] 0.08792496 0.4058160 0.078397033 0.04048708 0.3873750
## [10,] 0.08812404 0.4056475 0.078557622 0.04045552 0.3872153
## [11,] 0.08836304 0.4054716 0.078592181 0.04044474 0.3871284
## [12,] 0.08856613 0.4053527 0.078586046 0.04043058 0.3870646
## [13,] 0.08871685 0.4052791 0.078577325 0.04042696 0.3869998
## [14,] 0.08882119 0.4052319 0.078569539 0.04042964 0.3869478
## [15,] 0.08889398 0.4052017 0.078563418 0.04043043 0.3869105
## [16,] 0.08894236 0.4051833 0.078559113 0.04043024 0.3868850
## [17,] 0.08897310 0.4051726 0.078556465 0.04043003 0.3868678
## [18,] 0.08899235 0.4051665 0.078555006 0.04042975 0.3868564
## [19,] 0.08900464 0.4051628 0.078554238 0.04042936 0.3868490
## [20,] 0.08901262 0.4051604 0.078553819 0.04042900 0.3868442
## [21,] 0.08901785 0.4051588 0.078553585 0.04042874 0.3868410
## [22,] 0.08902129 0.4051577 0.078553448 0.04042857 0.3868390
## [23,] 0.08902359 0.4051570 0.078553359 0.04042846 0.3868376
## [24,] 0.08902513 0.4051565 0.078553295 0.04042839 0.3868367
```

```
## [25,] 0.08902617 0.4051561 0.078553247 0.04042834 0.3868361
```

```
plot(vardecomp)
```

5 Does an exogenous increase in prison cause crime to decrease?

Assuming all assumptions are correct, yes. The IRF shows a clear decrease in crime after a positive shock in the prison population.

6 Differences

Using first differences comes with advantages and disadvantages. One of the main advantages is it is more likely to be stationary for data that while declining/growing at a constant percentage rate, but changing absolute rate. In this case, that is true, so it is more likely to be stationary. It also results in improved small sample properties and avoids nonstandard distributions. The disadvantage of estimating in differences is that it does not allow you to include more long run relationships, as estimating in levels does not ignore those relationships.

7 Extra Credit

How can an impulse response function show the effect of an exogenous increase in the prison population on murder, etc., when prison population is an endogenous variable?

This mostly depends on the nature of the situation itself. An impulse to crime would take quite a while to effect the prison population, as sentencing and legal proceedings cause significant delay. On the other hand, an increase in the prison population could have an immediate impact on crime. If it is credible than an impulse in one could effect the other, impulse response functions are credible. If this was reversed, and we did an impulse on crime, it would not be as credible and could only really be seen to effect crime itself with reguard to short term changes.

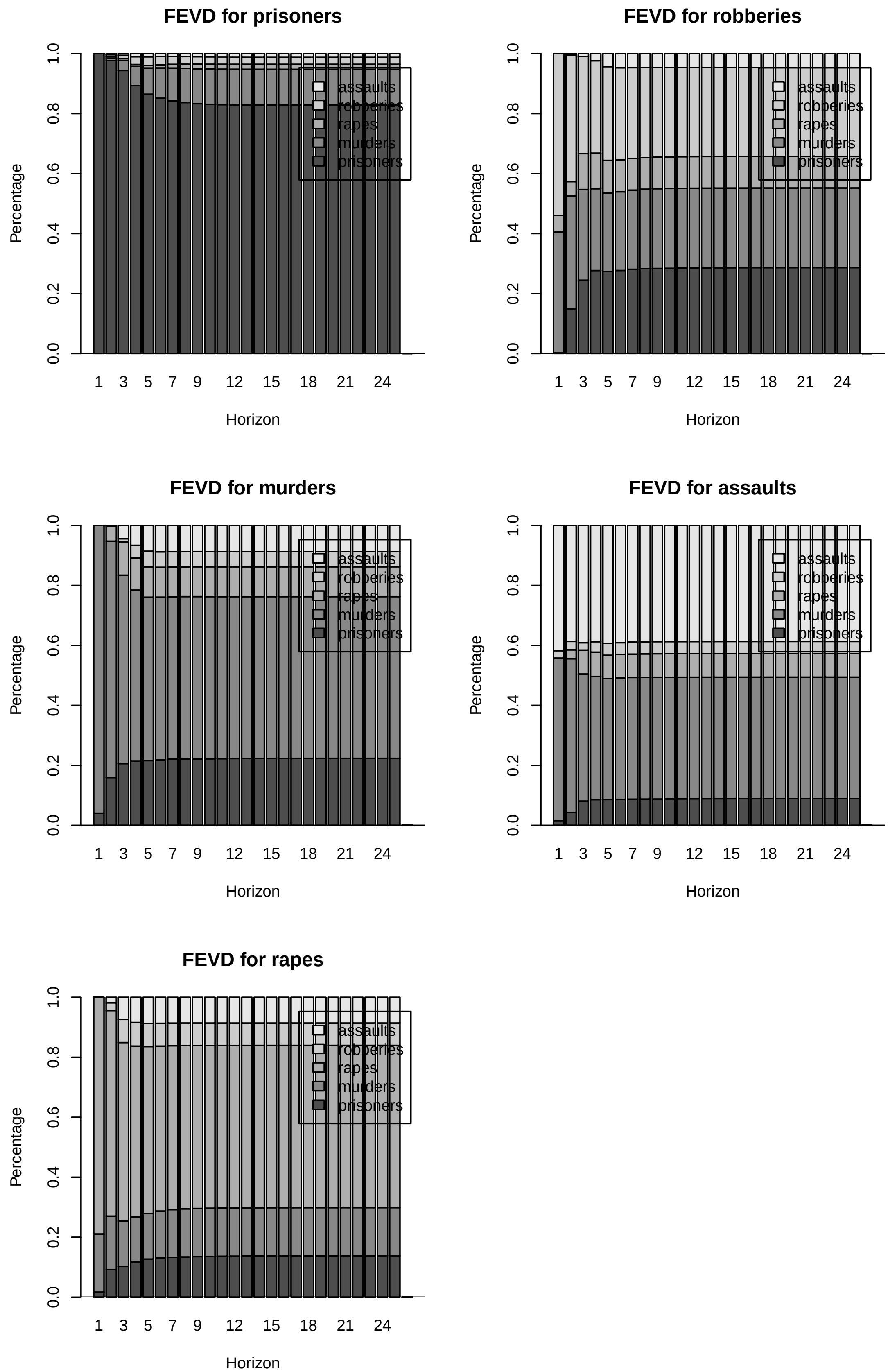

Figure 11: Variance Decomposition