MSD 2019 Final Project

A replication and extension of Chilling Effects: Online Surveillance and Wikipedia Use by Jonathon W. Penney, Berkeley Technology Law Journal

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Contents

1. Introduction

This Rmd file attempts to replicate and extend the results in Chilling Effects: Online Surveillance and Wikipedia Use by Jonathon W. Penney in Berkeley Technology Law Journal. The author is a research fellow at University of Toronto. This single author paper has H5-index of 21. This paper is about the NSA/PRISM surveillance 2007, where United States National Security Agency (NSA) started collecting Internet communications from various US Internet companies. This information was made public in 2013 by Edward Snowden revelations. This paper deals with the NSA paranoia where the paper studies traffic to Wikipedia articles on topics that raise privacy concerns for Wikipedia users before and after the Edward Snowden revelations. The Wikipedia traffic was chosen because over 50% of Internet users use Wikipedia as a source of information. Over 1/3 of Americans annually access Wikipedia as a source of information and is in top 10 of most popular sites on the internet.

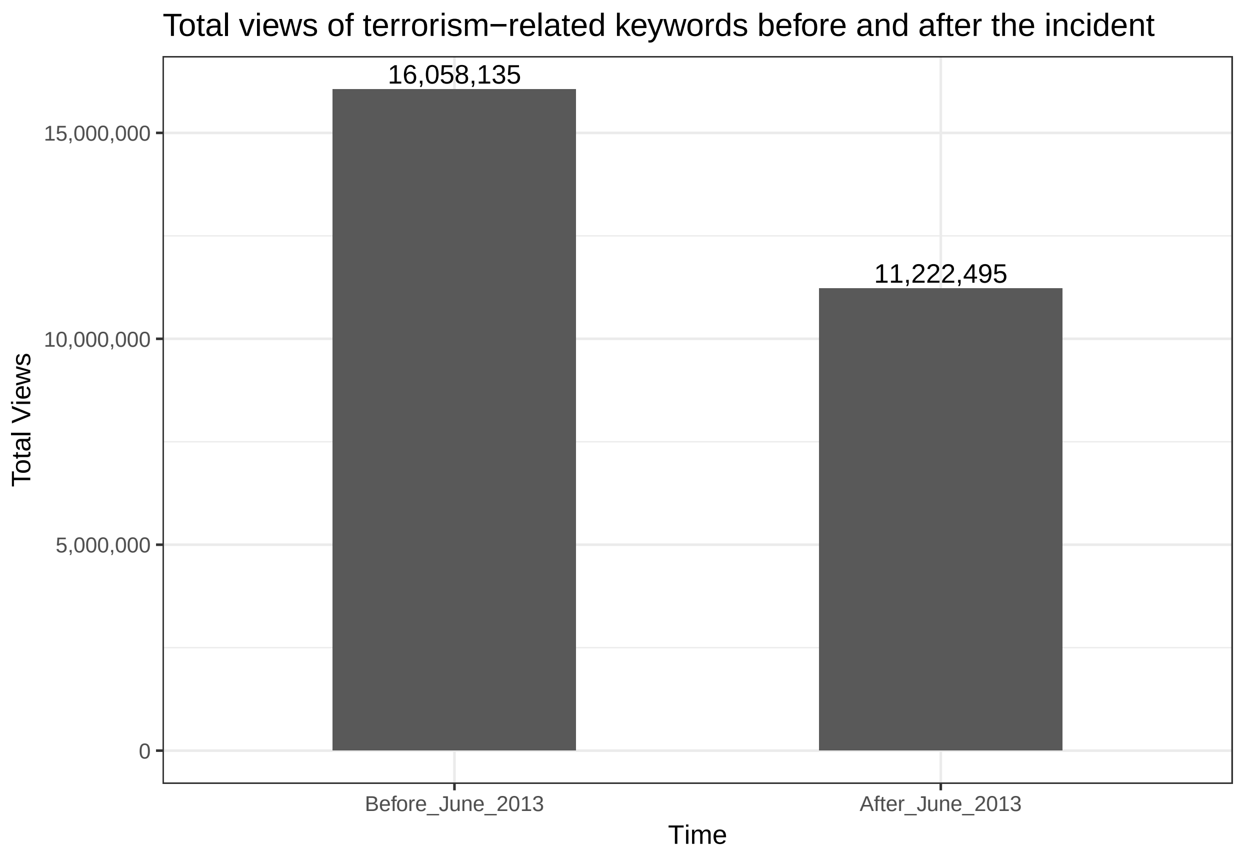
2. Reproducing the Original Study

```
load("data/terrorism_data.RData")
load("data/infra_data.RData")
load("data/popular_data.RData")
```

2.1 Total views of terrorism-related keywords before and after the incident

```
terrorism_data %>%
  mutate(before_after = ifelse(date < '2013-06-01', "Before_June_2013", "After_June_2013")) %>%
  group_by(before_after) %>%
  summarise(total_views = sum(views)) %>%
```

```r
  ggplot(aes(x= factor(before_after, level = c("Before_June_2013", "After_June_2013")), y=total_views, 
  scale_y_continuous(name="Total Views", labels = comma) +
  xlab("Time") +
  geom_text(aes(label=comma(total_views)), vjust=-0.3, color="black", size=3.5) +
  theme_bw(base_size = 10) +
  geom_bar(stat="identity") +
  ggtitle("Total views of terrorism-related keywords before and after the incident")
```



2.2 Linear model with interactions: Analysis and Plots

```r
lm_plot_topic <- function(input_df, gg_title){

df <- data.frame(input_df)
df <- df %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
df$surveillence <- 'before'
df$surveillence[df$month >= '2013-06-01'] <- 'after'

model <- lm(views ~ month + surveillence + month*surveillence, data = df)
print(summary(model))


df$prediction <- predict(model, df)
df$se <- predict(model, df,
```

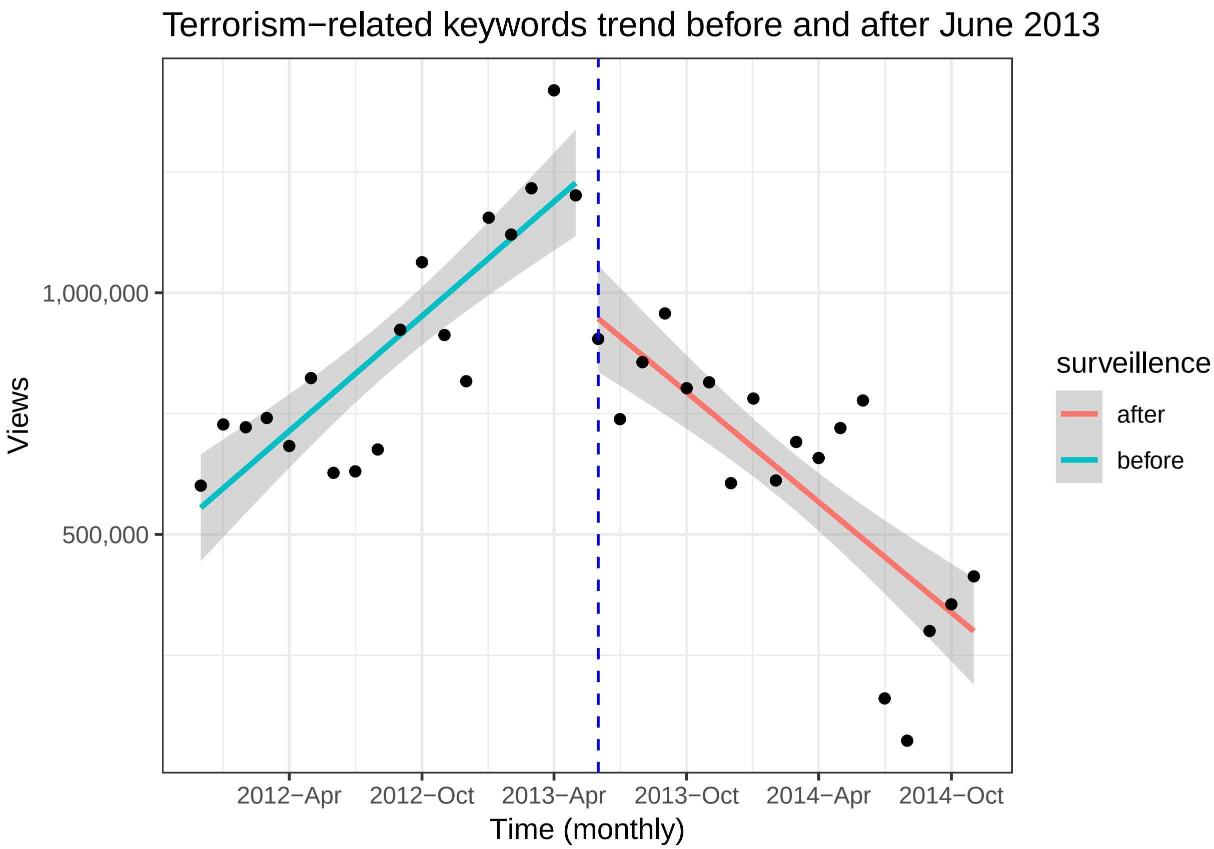
```r
                      se.fit = TRUE)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
df$LoCI <- df$prediction - z.val * df$se
df$HiCI <- df$prediction + z.val * df$se

df$month <- ymd(df$month)

ggplot(df,
       aes(x = month,
           y = prediction)) +
  geom_smooth(aes(ymin = LoCI,
                  ymax = HiCI,
                  color = surveillence),
              stat = "identity") +
  geom_point(data = df, aes(x=month, y = views)) +
  geom_vline(xintercept = as.Date('2013-06-01'), linetype = 2, colour = 'blue') +
  ylab('Views') +
  xlab('Time (monthly)') +
  scale_x_date(date_breaks = "6 month", labels = date_format("%Y-%b")) +
  scale_y_continuous(labels = comma) +
  ggtitle(gg_title)
}
```

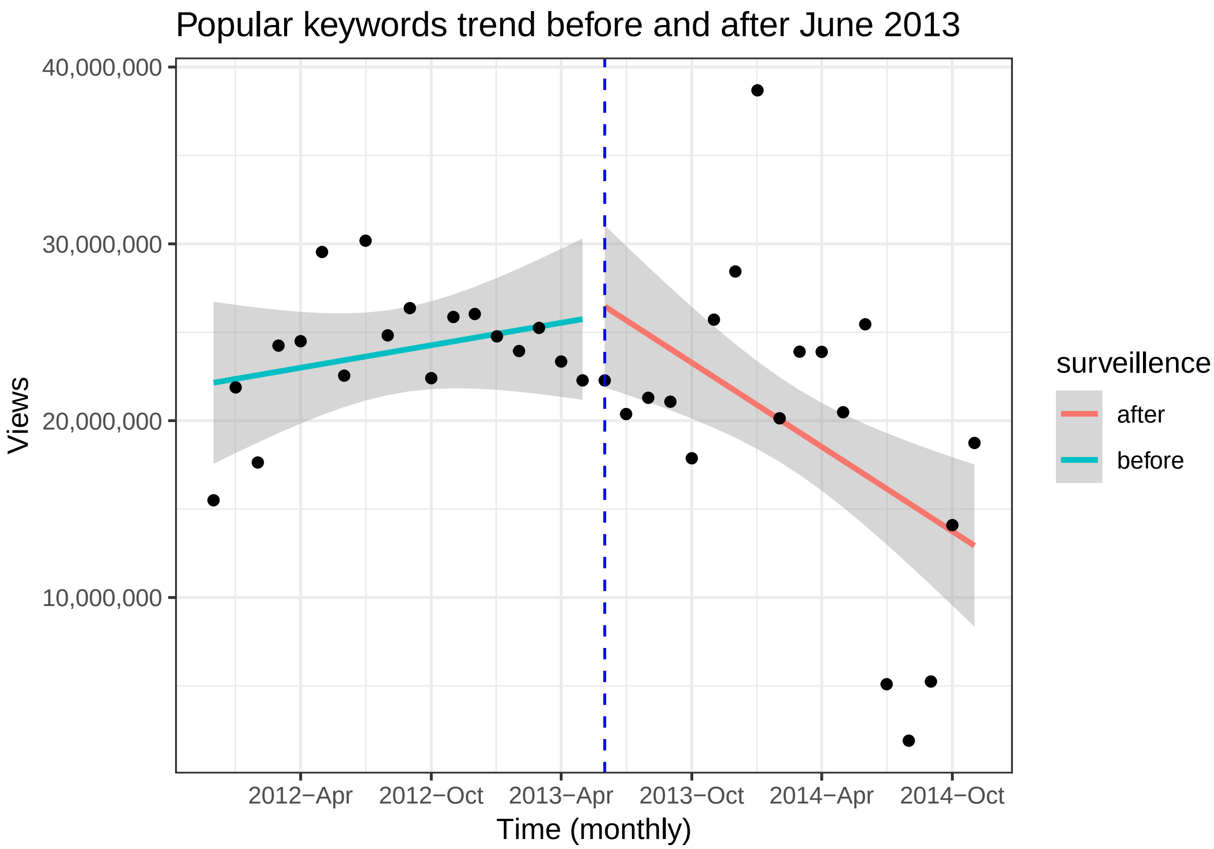
```r
lm_plot_topic(terrorism_data, 'Terrorism-related keywords trend before and after June 2013')
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -341385  -76768   13782   87116  286130
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                2.074e+07  3.568e+06   5.813 1.87e-06 ***
## month                     -1.248e+03  2.214e+02  -5.638 3.10e-06 ***
## surveillencebefore        -4.008e+07  4.958e+06  -8.083 3.14e-09 ***
## month:surveillencebefore   2.548e+03  3.129e+02   8.142 2.68e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 148200 on 32 degrees of freedom
## Multiple R-squared:  0.7498, Adjusted R-squared:  0.7263
## F-statistic: 31.96 on 3 and 32 DF,  p-value: 9.546e-10
```



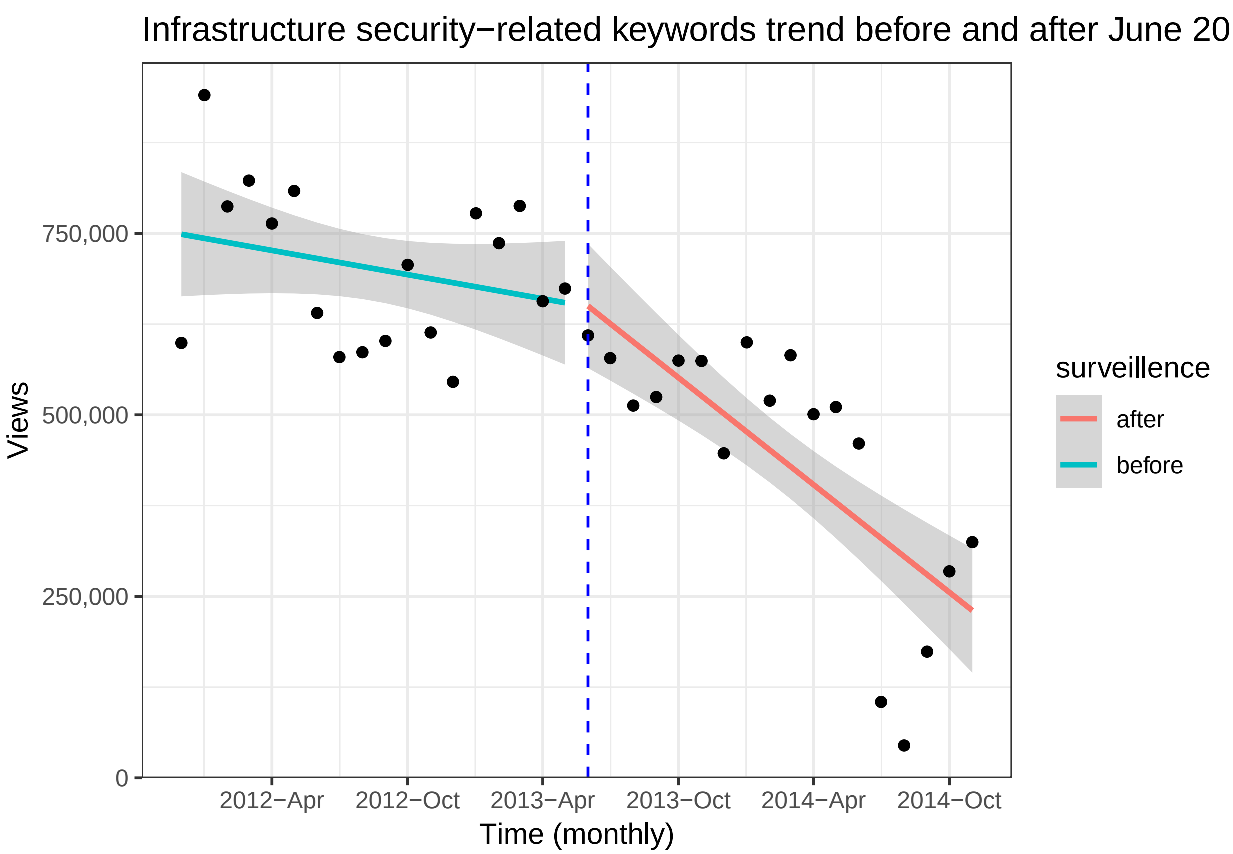

```
lm_plot_topic(popular_data, 'Popular keywords trend before and after June 2013')
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -13436279  -3492306     -1164   2864260  17808433
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               440615805  148068036   2.976  0.00553 **
## month                        -26118       9187  -2.843  0.00772 **
## surveillencebefore       -524944327  205785253  -2.551  0.01573 *
## month:surveillencebefore      33073      12987   2.547  0.01589 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6152000 on 32 degrees of freedom
## Multiple R-squared:  0.288,  Adjusted R-squared:  0.2212
## F-statistic: 4.314 on 3 and 32 DF,  p-value: 0.01155
```




```
lm_plot_topic(infra_data, 'Infrastructure security-related keywords trend before and after June 2013')
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -260393  -78202   21543   91386  197325
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)              13488540.4  2763780.6   4.880 2.81e-05 ***
## month                        -809.7      171.5  -4.721 4.46e-05 ***
## surveillencebefore       -9948117.6  3841107.8  -2.590   0.0143 *
## month:surveillencebefore      627.3      242.4   2.588   0.0144 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 114800 on 32 degrees of freedom
## Multiple R-squared:  0.6862, Adjusted R-squared:  0.6567
## F-statistic: 23.32 on 3 and 32 DF,  p-value: 3.434e-08
```



3. Extended Analysis

3.1 Longer Trend Analysis

3.2 Per-keyword Analysis

```
lm_plot_keyword <- function(input_df, article_name, gg_title){

df <- data.frame(input_df)
df <- df %>%
  group_by(article ,month=floor_date(date, "month")) %>%
  summarize(views=sum(views)) %>%
  filter(article == article_name)

df$surveillence <- 'before'
df$surveillence[df$month >= '2013-06-01'] <- 'after'

model <- lm(views ~ month + surveillence + month*surveillence, data = df)
print(summary(model))


df$prediction <- predict(model, df)
df$se <- predict(model, df,
                      se.fit = TRUE)$se.fit
```

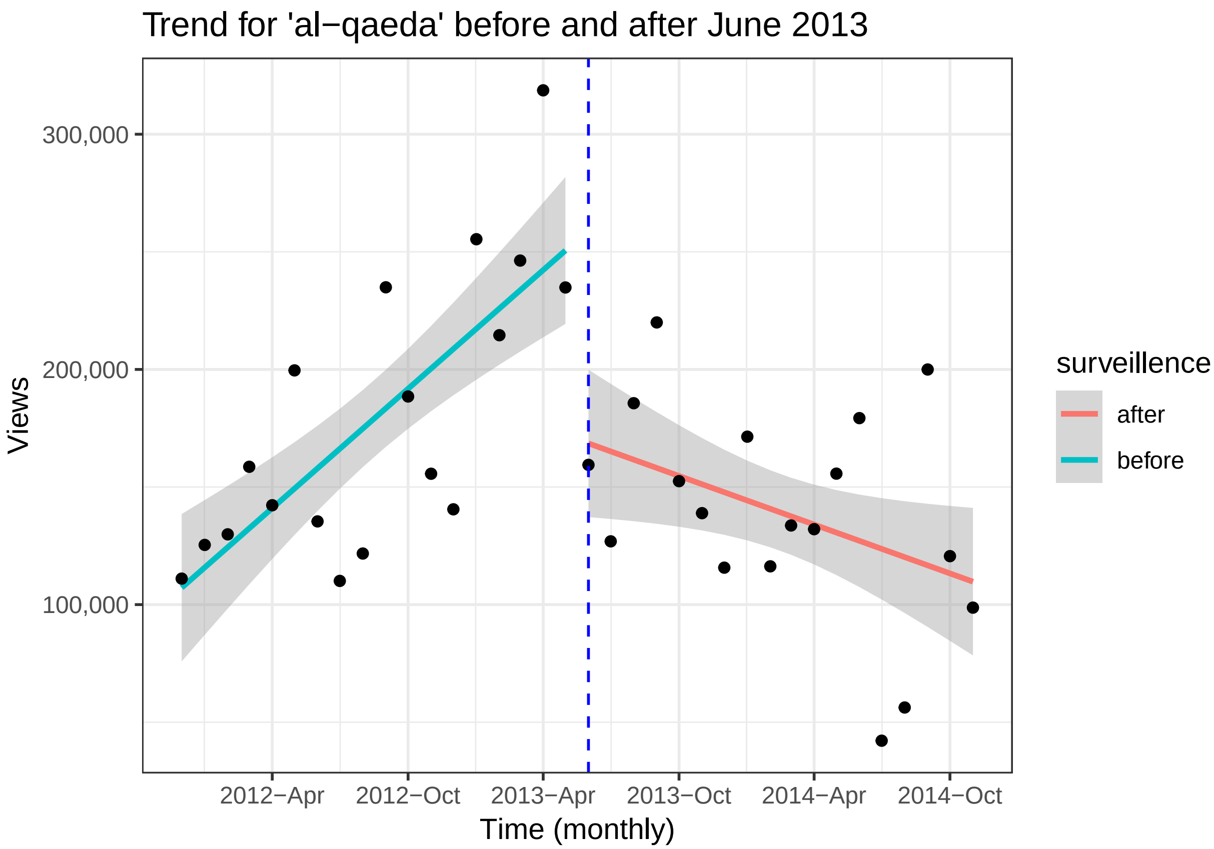
```r
z.val <- qnorm(1 - (1 - 0.90)/2)
df$LoCI <- df$prediction - z.val * df$se
df$HiCI <- df$prediction + z.val * df$se

df$month <- ymd(df$month)

ggplot(df,
       aes(x = month,
           y = prediction)) +
  geom_smooth(aes(ymin = LoCI,
                  ymax = HiCI,
                  color = surveillence),
              stat = "identity") +
  geom_point(data = df, aes(x=month, y = views)) +
  geom_vline(xintercept = as.Date('2013-06-01'), linetype = 2, colour = 'blue') +
  ylab('Views') +
  xlab('Time (monthly)') +
  scale_x_date(date_breaks = "6 month", labels = date_format("%Y-%b")) +
  scale_y_continuous(labels = comma) +
  ggtitle(gg_title)
}
```

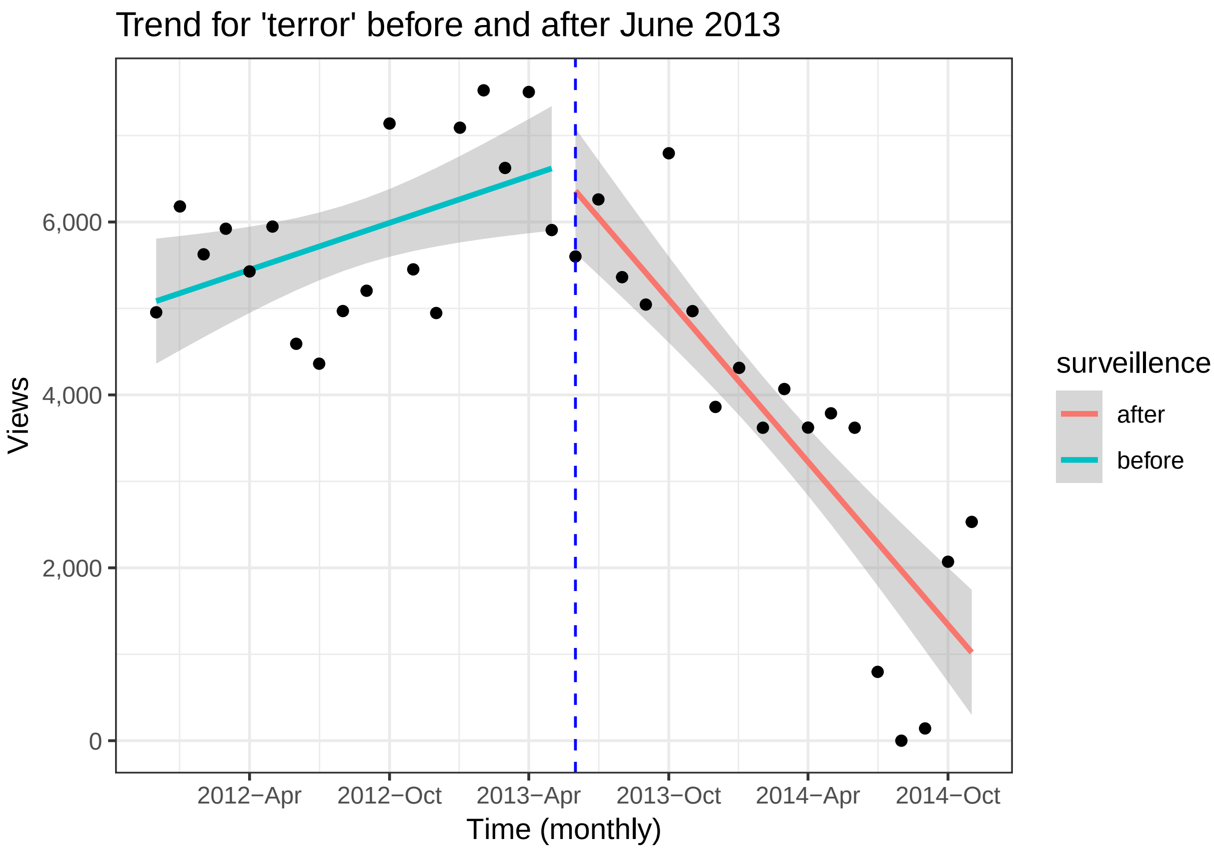
```r
lm_plot_keyword(terrorism_data, 'al-qaeda', 'Trend for \'al-qaeda\' before and after June 2013')
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -81582 -23037  -2093  25332  83296
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                1.969e+06  1.013e+06   1.943 0.060805 .
## month                     -1.135e+02  6.285e+01  -1.806 0.080314 .
## surveillencebefore        -6.107e+06  1.408e+06  -4.338 0.000134 ***
## month:surveillencebefore   3.909e+02  8.884e+01   4.400 0.000113 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 42080 on 32 degrees of freedom
## Multiple R-squared:  0.4909, Adjusted R-squared:  0.4432
## F-statistic: 10.29 on 3 and 32 DF,  p-value: 6.776e-05
```



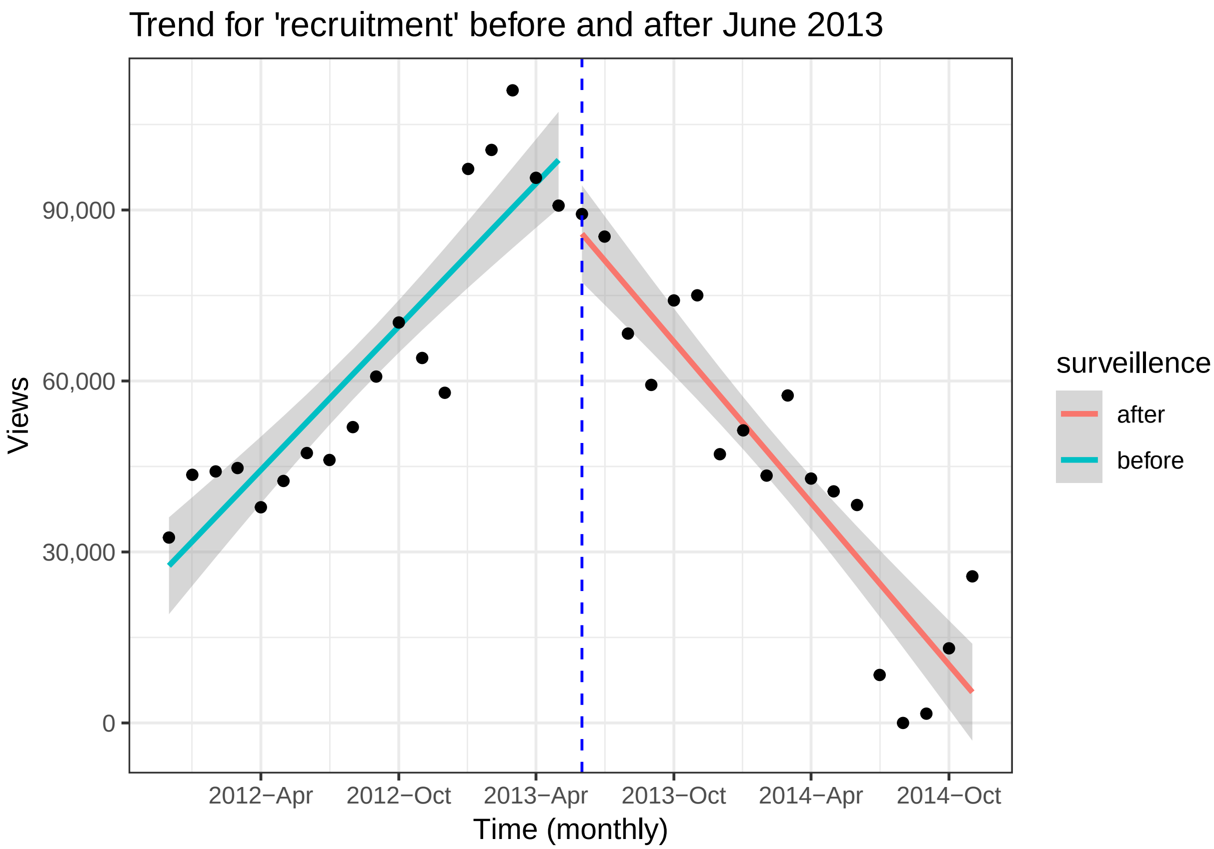

```r
lm_plot_keyword(terrorism_data, 'terror', 'Trend for \'terror\' before and after June 2013')
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1969.2  -700.2   172.0   754.2  1692.1
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 1.698e+05  2.337e+04   7.268 2.94e-08 ***
## month                      -1.031e+01  1.450e+00  -7.110 4.56e-08 ***
## surveillencebefore         -2.102e+05  3.247e+04  -6.473 2.78e-07 ***
## month:surveillencebefore    1.328e+01  2.049e+00   6.479 2.73e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 970.8 on 32 degrees of freedom
## Multiple R-squared:  0.7564, Adjusted R-squared:  0.7336
## F-statistic: 33.13 on 3 and 32 DF,  p-value: 6.22e-10
```




```r
lm_plot_keyword(terrorism_data, 'recruitment', 'Trend for \'recruitment\' before and after June 2013')
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20046.9  -8343.9    843.7   7445.4  20621.8
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               2.548e+06  2.745e+05   9.282 1.36e-10 ***
## month                    -1.553e+02  1.703e+01  -9.116 2.07e-10 ***
## surveillencebefore       -4.629e+06  3.815e+05 -12.132 1.64e-13 ***
## month:surveillencebefore  2.930e+02  2.408e+01  12.169 1.52e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11410 on 32 degrees of freedom
## Multiple R-squared:  0.8417, Adjusted R-squared:  0.8268
## F-statistic:  56.7 on 3 and 32 DF,  p-value: 6.647e-13
```



3.3 Time-series Analysis

3.4 Trend Recovery

The following is a list of all packages used to generate these results. (Leave at very end of file.)

```
sessionInfo()
```

```
## R version 3.5.1 (2018-07-02)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS  10.14.4
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] bindrcpp_0.2.2       wikipediatrend_2.1.1 lubridate_1.7.4
##  [4] forcats_0.3.0        stringr_1.4.0        dplyr_0.7.7
##  [7] purrr_0.2.5          readr_1.1.1          tidyr_0.8.1
```

```
## [10] tibble_2.1.1        ggplot2_3.1.1       tidyverse_1.2.1
## [13] scales_1.0.0
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_1.0.1       cellranger_1.1.0 compiler_3.5.1   pillar_1.3.1
##  [5] plyr_1.8.4       bindr_0.1.1      tools_3.5.1      digest_0.6.18
##  [9] jsonlite_1.6     evaluate_0.12    nlme_3.1-137     gtable_0.3.0
## [13] lattice_0.20-35  pkgconfig_2.0.2  rlang_0.3.4      cli_1.1.0
## [17] rstudioapi_0.8   yaml_2.2.0       haven_1.1.2      hellno_0.0.1
## [21] withr_2.1.2      xml2_1.2.0       httr_1.4.0       knitr_1.20
## [25] hms_0.4.2        rprojroot_1.3-2  grid_3.5.1       tidyselect_0.2.5
## [29] glue_1.3.1       R6_2.4.0         readxl_1.1.0     rmarkdown_1.10
## [33] modelr_0.1.2     magrittr_1.5     backports_1.1.2  htmltools_0.3.6
## [37] rvest_0.3.3      assertthat_0.2.1 colorspace_1.4-1 labeling_0.3
## [41] stringi_1.4.3    lazyeval_0.2.2   munsell_0.5.0    broom_0.5.0
## [45] crayon_1.3.4
```