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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2019-05-11 23:52:07

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

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

load("data/terrorism_data_long.RData")
```

2.1 Data

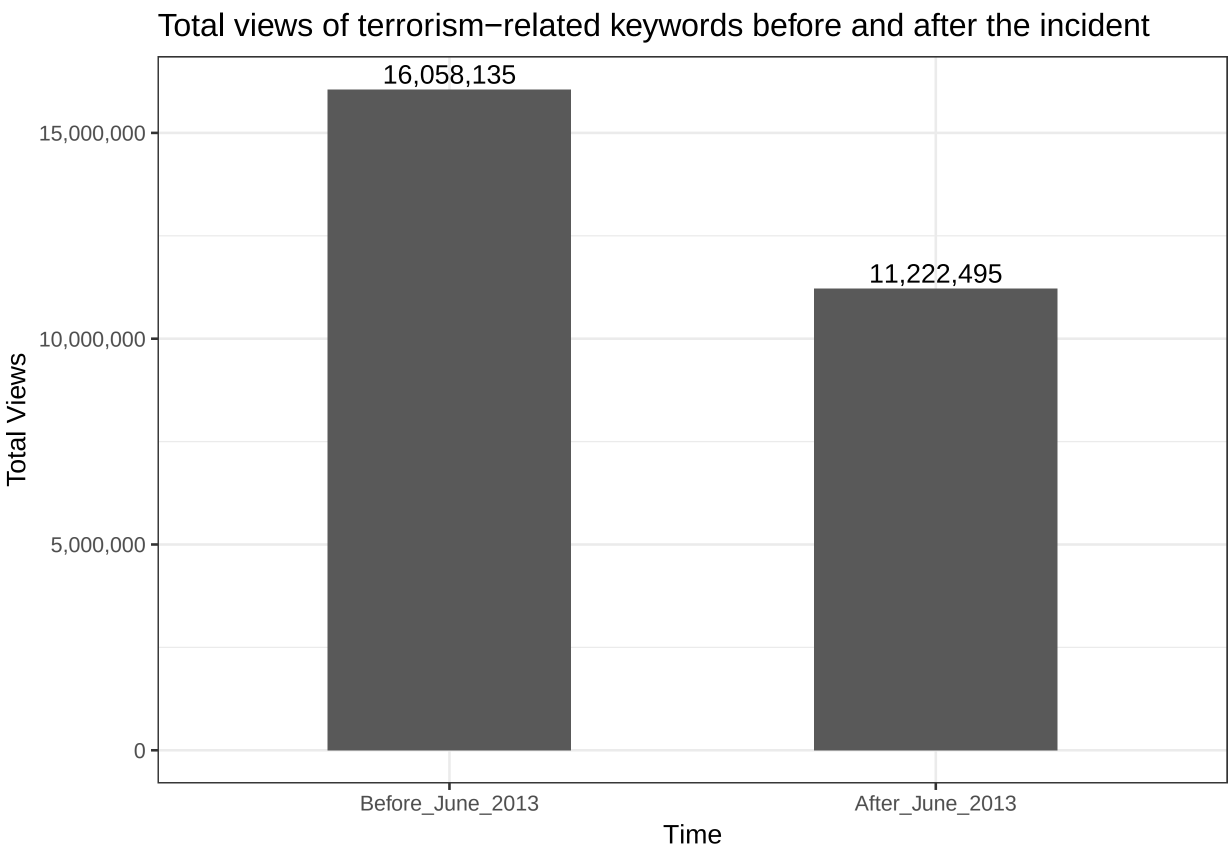
2.2 Methodology

2.3 Criticism

2.4 Replication Results

2.4.1 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)) %>%
  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")
```



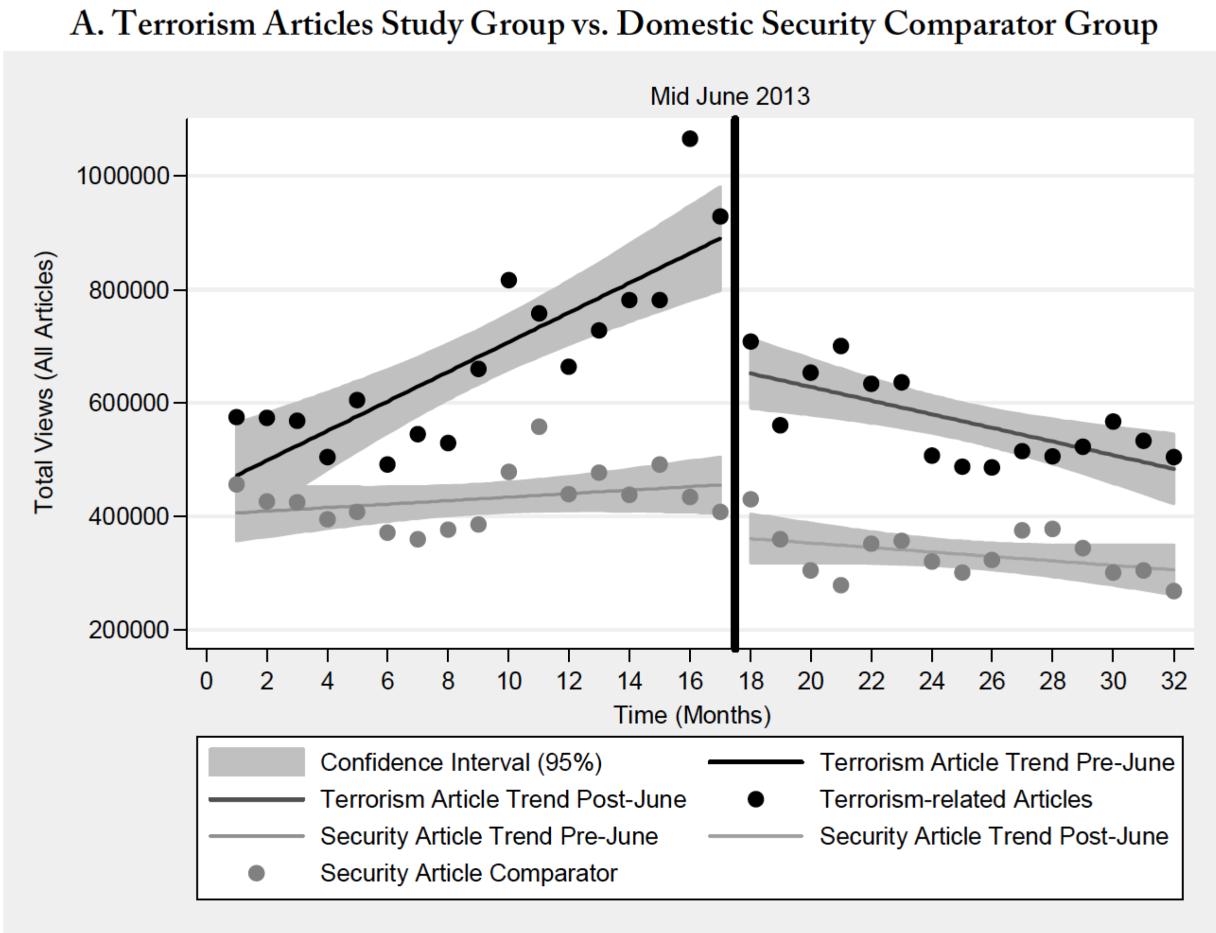


Figure 1: Original result for terrorism-related keywords

Table 2: Second Results, 47 Terrorism-related Articles (Hamas Excluded)

Independent Variable	Coefficients	Standard Error	*P*-value
Coefficient (β_0) Expected Total Views at Beginning of Study	**2289153****	109751.5	0.000
Secular trend in data (β_1) Change in Views (Monthly) Before 6/2013	**41420.51****	10710.65	0.001
Change in level (β_2) Change in Views Immediately After 6/2013	**–693616.9 ****	154640.9	0.000
Change in slope (β_3) Change in Views (Monthly) After 6/2013	**–67513.1****	16789.25	0.000

$^{*}p < 0.05$, $^{**}p < 0.01$

Figure 2: Original regression summary for terrorism-related keywords

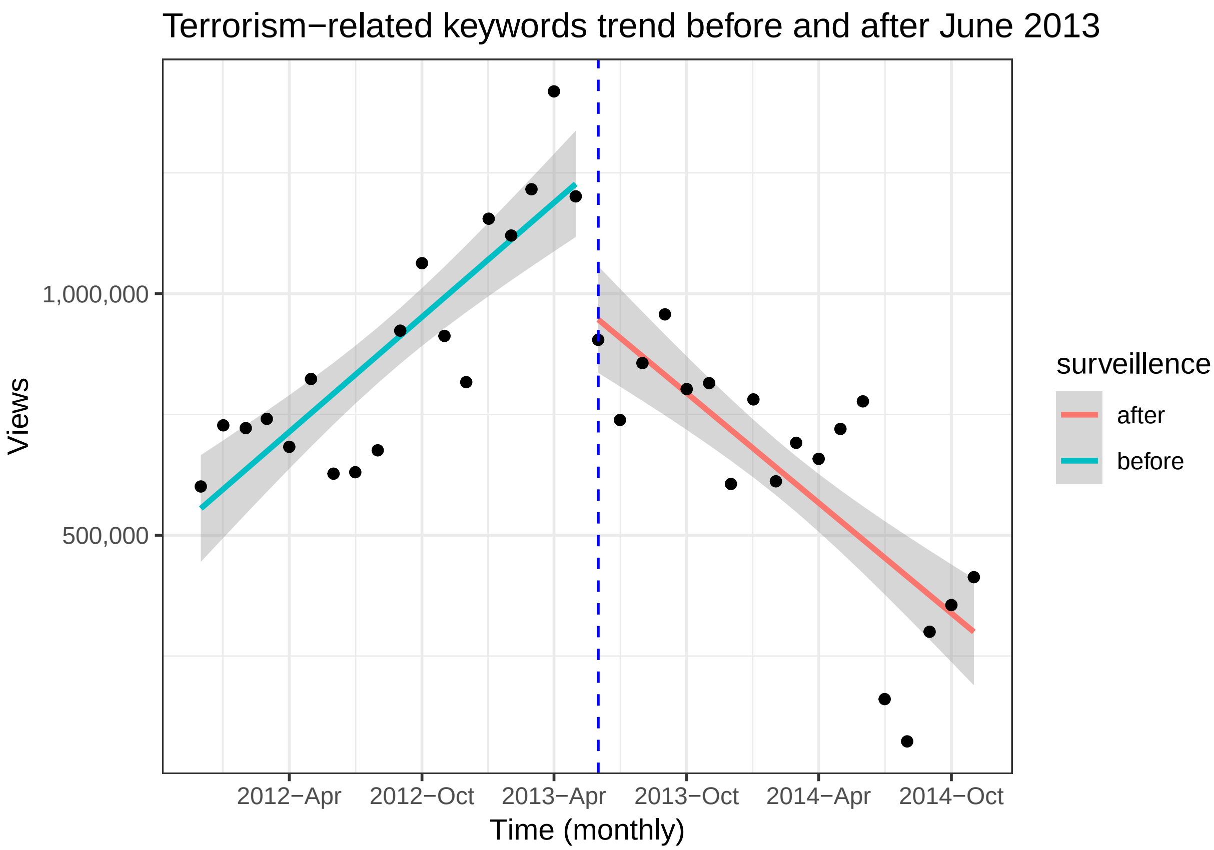
2.4.2 Linear model with interactions: Analysis and Plots

```
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,
                    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)
}
```

```
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 ***
```

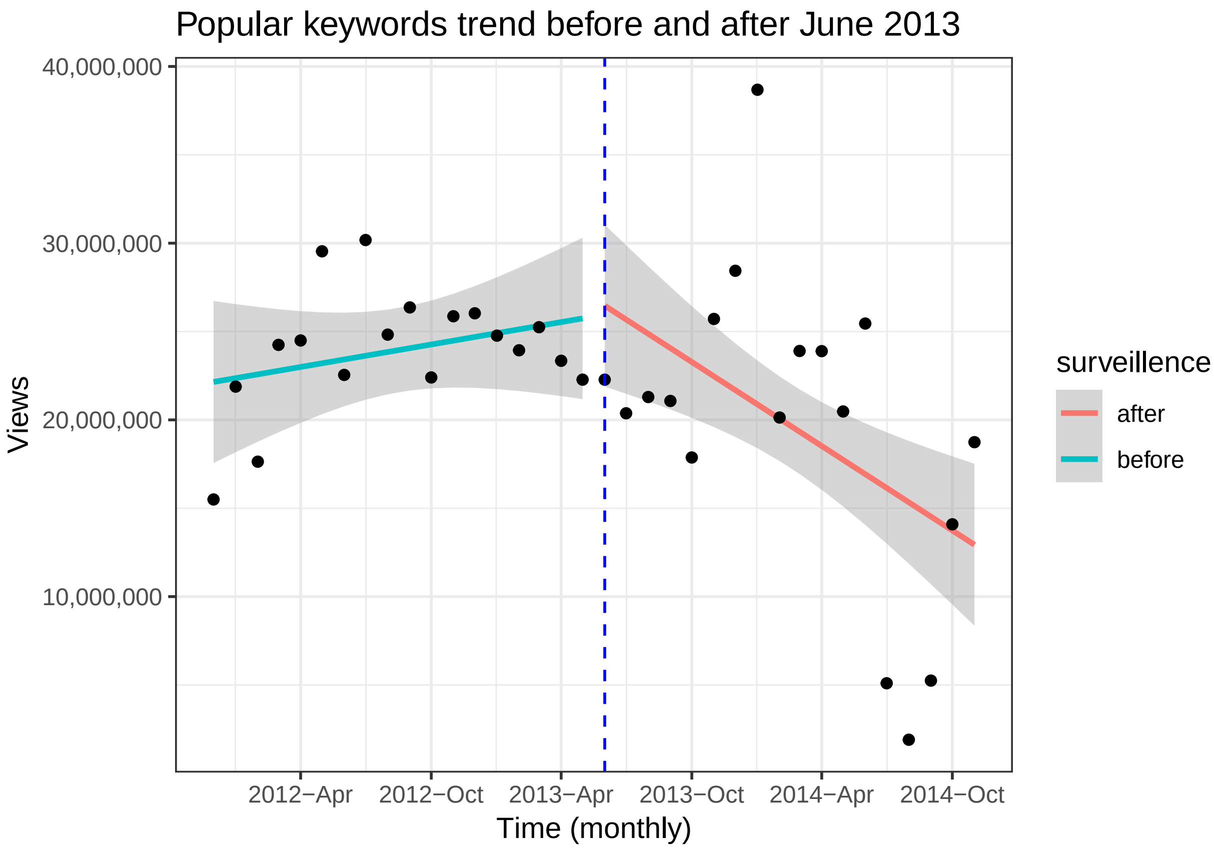
```
## month                      -1.248e+03  2.214e+02  -5.638 3.10e-06 ***
## surveillencebefore         -4.008e+07  4.958e+06  -8.083 3.14e-09 ***
## month:surveillencebefore  2.548e+03  3.129e+02   8.142 2.68e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual 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 *
```

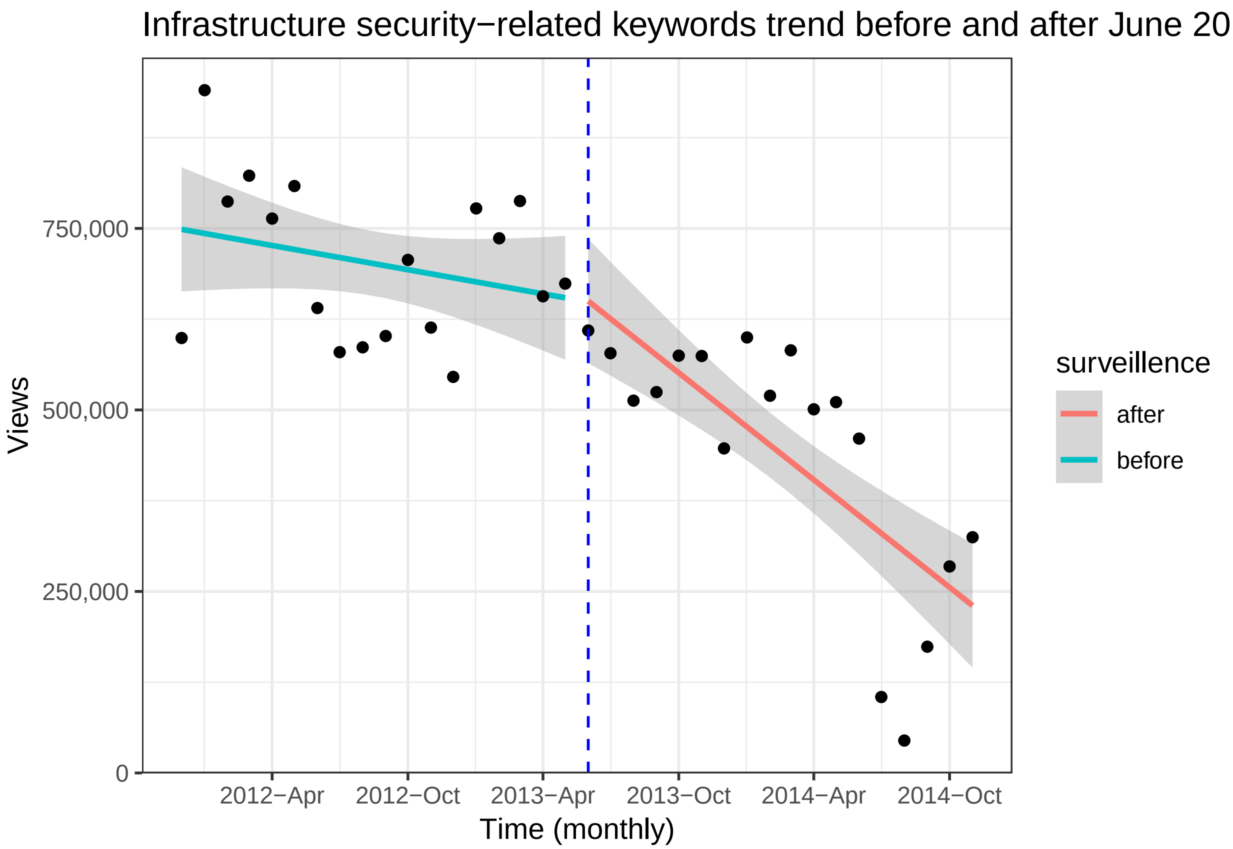
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6152000 on 32 degrees of freedom
## Multiple R-squared:  0.288,  Adjusted R-squared:  0.2212
## F-statistic: 4.314 on 3 and 32 DF,  p-value: 0.01155
```




```r
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

The link to our data broke on Saturday May 11th, 2019. Our original plots consisted data from 2012 to 2019. Our group tried to reconstruct the graph from data that was saved on our laptops before the link broke, which is until 2015. Luckly we have original graphs saved as png file. After each reproduced graphs, we included what they used to look like before the link broke, and full data was available.

```
monthly_agg <- terrorism_data_long %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
monthly_agg$surveillence <- 'before'
monthly_agg$surveillence[monthly_agg$month >= '2013-06-01'] <- 'after'
model <- lm(views ~ month + surveillence + month*surveillence, data = monthly_agg)
summary(model)
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = monthly_agg)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -376110  -77479   25547   74033  242163
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               4.829e+06  1.305e+06   3.701 0.000491 ***
## month                    -2.708e+02  8.004e+01  -3.383 0.001316 **
## surveillencebefore       -3.686e+06  1.793e+06  -2.056 0.044497 *
## month:surveillencebefore  2.417e+02  1.131e+02   2.137 0.036990 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 115400 on 56 degrees of freedom
## Multiple R-squared:  0.6412, Adjusted R-squared:  0.6219
## F-statistic: 33.35 on 3 and 56 DF,  p-value: 1.684e-12
```

```
monthly_agg$prediction <- predict(model, monthly_agg)
monthly_agg$se <- predict(model, monthly_agg,
                      se.fit = TRUE)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
monthly_agg$LoCI <- monthly_agg$prediction - z.val * monthly_agg$se
monthly_agg$HiCI <- monthly_agg$prediction + z.val * monthly_agg$se
monthly_agg$month <- ymd(monthly_agg$month)
ggplot(monthly_agg,
       aes(x = month,
           y = views)) +
  geom_point(data = monthly_agg, aes(x=month, y = views)) +
  geom_vline(xintercept = as.Date('2013-06-01'), linetype = 2, colour = 'blue') +
  geom_vline(xintercept = as.Date('2014-12-31'), linetype = 2, colour = 'blue') +
  ylab('Views') +
  xlab('Time (monthly)') +
  scale_x_date(date_breaks = "6 month", labels = date_format("%Y-%b")) +
   theme_bw(base_size = 5) +
  scale_y_continuous(labels = comma)
```

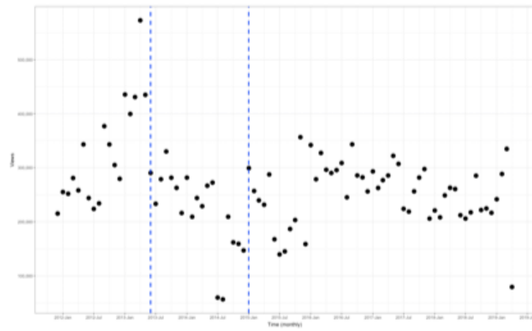
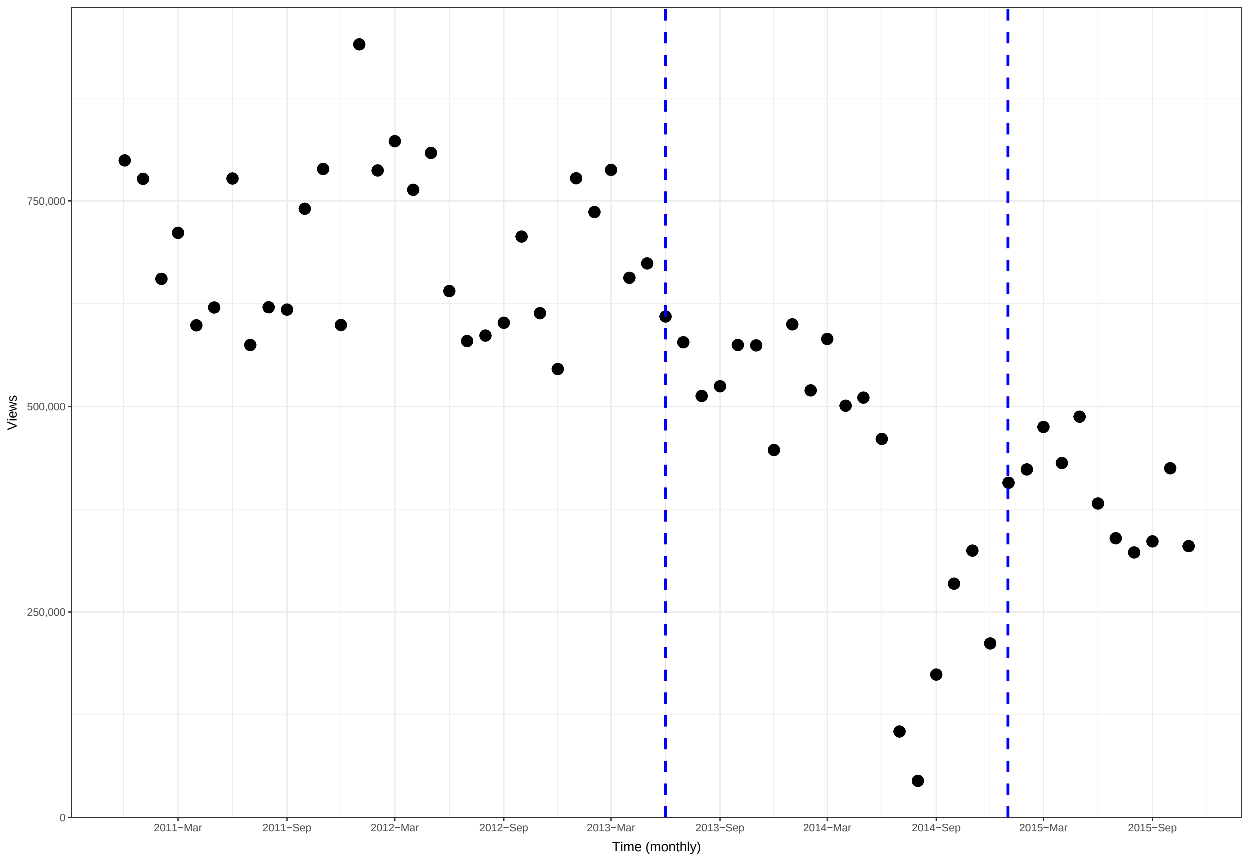


Figure 3: Original Scatter Plot with full data

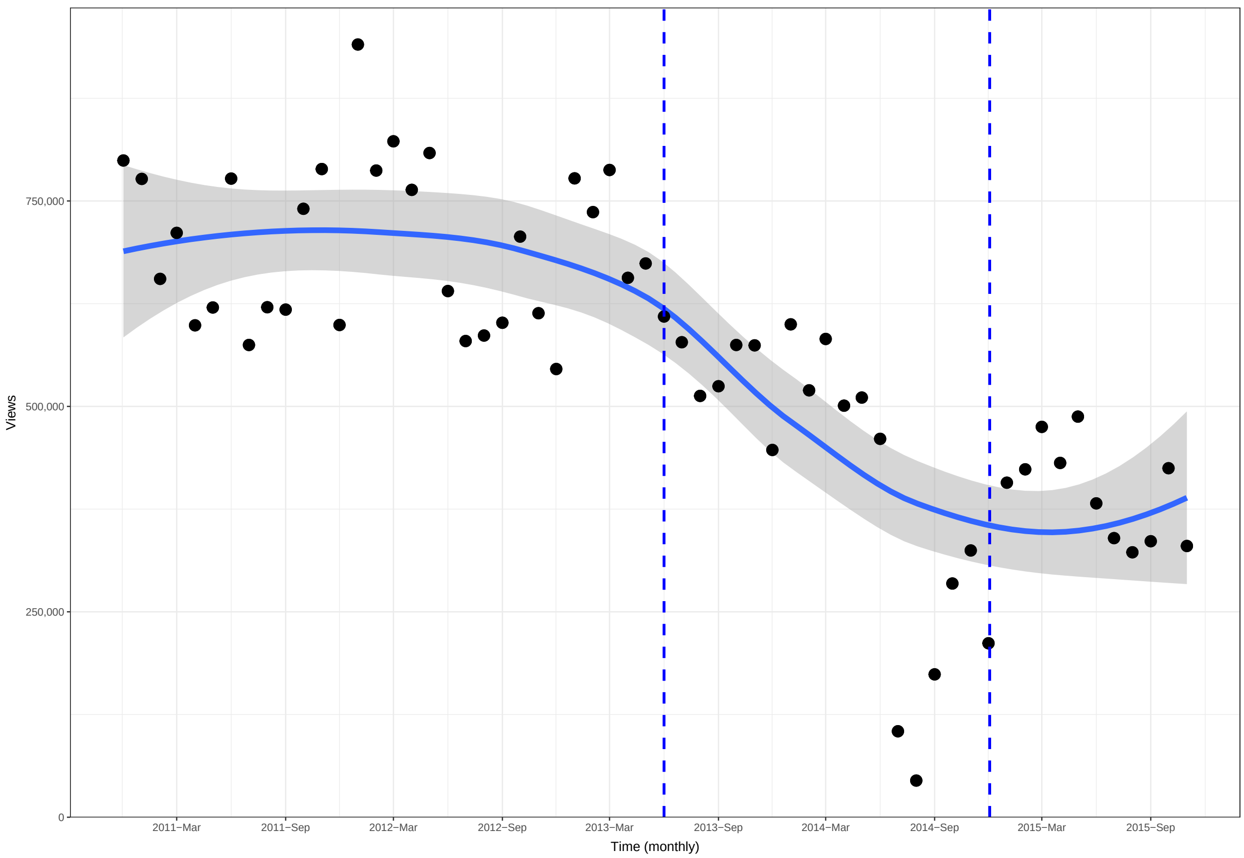


First, we take out all the line graphs, and plot scattered graph according to data. The original graph with full data is shown above.

```
monthly_agg <- terrorism_data_long %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
monthly_agg$surveillence <- 'before'
monthly_agg$surveillence[monthly_agg$month >= '2013-06-01'] <- 'after'

model <- lm(views ~ month + surveillence + month*surveillence, data = monthly_agg)
monthly_agg$prediction <- predict(model, monthly_agg)
monthly_agg$se <- predict(model, monthly_agg,
                          se.fit = TRUE)$se.fit
```

```r
z.val <- qnorm(1 - (1 - 0.90)/2)
monthly_agg$LoCI <- monthly_agg$prediction - z.val * monthly_agg$se
monthly_agg$HiCI <- monthly_agg$prediction + z.val * monthly_agg$se
monthly_agg$month <- ymd(monthly_agg$month)
ggplot(monthly_agg,
       aes(x = month,
           y = views)) + geom_point()+stat_smooth( se=T)+
  geom_point(data = monthly_agg, aes(x=month, y = views)) +
  geom_vline(xintercept = as.Date('2013-06-01'), linetype = 2, colour = 'blue') +
  geom_vline(xintercept = as.Date('2014-12-3'), linetype = 2, colour = 'blue') +
  ylab('Views') +
  xlab('Time (monthly)') +
  scale_x_date(date_breaks = "6 month", labels = date_format("%Y-%b")) +
  theme_bw(base_size = 5) +
  scale_y_continuous(labels = comma)
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Then, our group had fit a polynomial surface determined by one or more numerical predictors, using local fitting. The graph also displays confidence interval around as gray. The graph below shows rise in trend from 2015 January to July 2016. The graph trend again drops from July 2016 to Jan 2019. The views counts are similar at the beginning of 2016 and end of plot at 2019. This shows that there has been a "trend reovery," but the trend again drops without second "Snowden Revelation." This may mean that the decrease in trend from 2013 to 2015 may be due to other factors rather than due to NSA paranoia.

The original graph with full data is shown below.

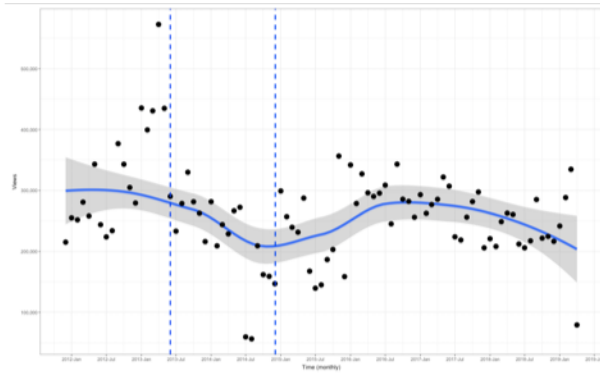


Figure 4: Original Stat Smooth Curve with full data

```
monthly_agg <- terrorism_data_long %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
monthly_agg$surveillence <- 'before'
monthly_agg$surveillence[monthly_agg$month >= '2013-06-01'] <- 'after'
model <- lm(views ~ month + surveillence + month*surveillence, data = monthly_agg)
monthly_agg$prediction <- predict(model, monthly_agg)
monthly_agg$se <- predict(model, monthly_agg,
                          se.fit = TRUE)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
monthly_agg$LoCI <- monthly_agg$prediction - z.val * monthly_agg$se
monthly_agg$HiCI <- monthly_agg$prediction + z.val * monthly_agg$se
monthly_agg$month <- ymd(monthly_agg$month)
monthly_agg$month <- as.numeric(monthly_agg$month)
fit <- lm(views~poly(month,4,raw=TRUE),monthly_agg)
plot(views~month,monthly_agg)
curve(predict(fit,newdata=data.frame(month=x)),add=T)
```

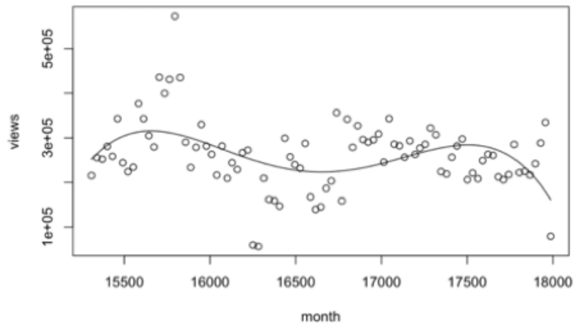
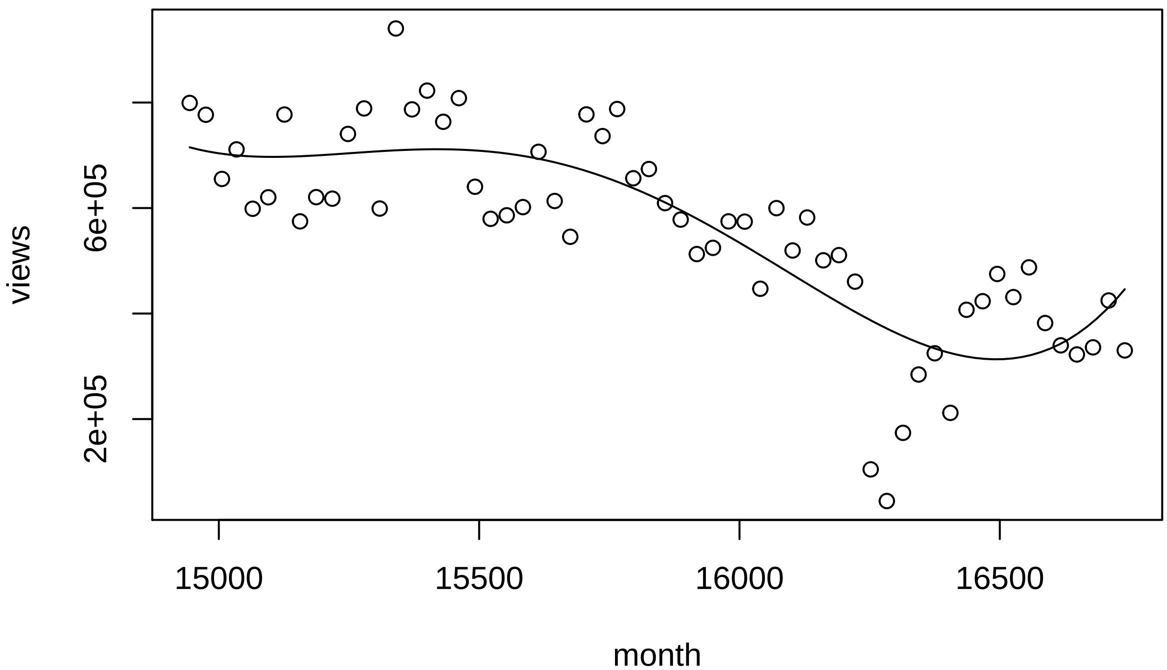


Figure 5: Original Polynomial curve n4 with full data



Then, our group had went further and fit a polynomial graph of degree 4. The curve above shows that there is sharper decrease in trend at the end of graph, far from 2013 region. This again backs our claim that there is a decrease in 2018 to 2019 without another "Snowden Revelation." This means the decrease in trend after 2013 can be attributed to another resason than Snowden Revelation.

```
monthly_agg <- terrorism_data_long %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
monthly_agg$surveillence <- 'before'
monthly_agg$surveillence[monthly_agg$month >= '2013-06-01'] <- 'after'

model <- lm(views ~ month + surveillence + month*surveillence, data = monthly_agg)
monthly_agg$prediction <- predict(model, monthly_agg)
monthly_agg$se <- predict(model, monthly_agg,
                         se.fit = TRUE)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
monthly_agg$LoCI <- monthly_agg$prediction - z.val * monthly_agg$se
monthly_agg$HiCI <- monthly_agg$prediction + z.val * monthly_agg$se
```

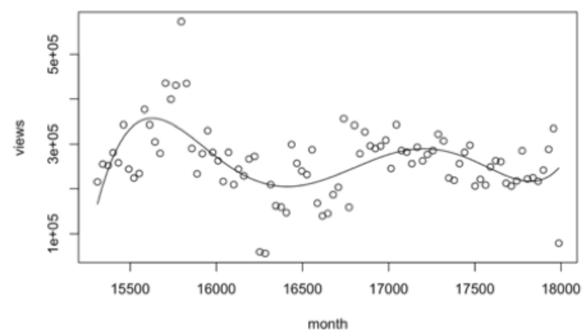
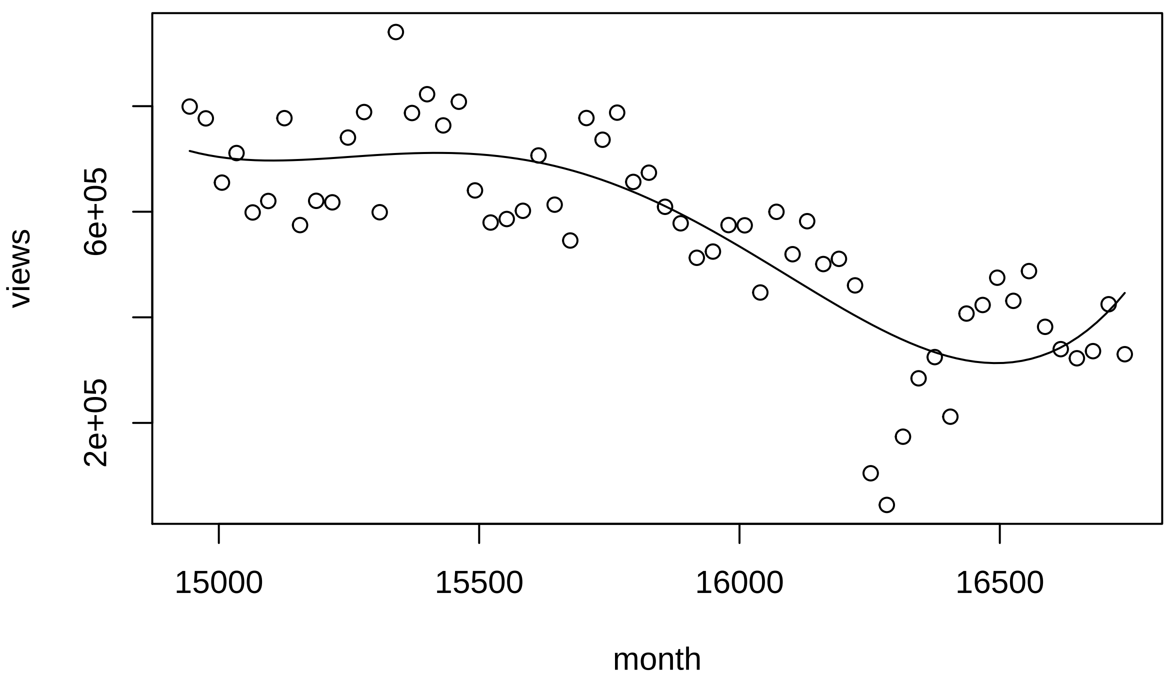


Figure 6: Original Polynomial curve n5 with full data

```
monthly_agg$month <- ymd(monthly_agg$month)
monthly_agg$month <- as.numeric(monthly_agg$month)
fit <- lm(views~poly(month,5,raw=TRUE),monthly_agg)
plot(views~month,monthly_agg)
curve(predict(fit,newdata=data.frame(month=x)),add=T)
```

```
## Warning in predict.lm(fit, newdata = data.frame(month = x)): prediction
## from a rank-deficient fit may be misleading
```



Then, our group had went further and fit a polynomial graph of degree 5 instead of 4. This may be overfitting, but wanted to analyze the graph to full extent. This graph also shows that there has been decrease in trend from 2018 to 2019, but end of the trend is actually increasing. This fluctuating trend shows that author of original paper's claim that chilling effect is not caused due to NSA paranoia.

```
monthly_agg <- terrorism_data_long %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
monthly_agg$surveillence <- 'before'
```

```r
monthly_agg$surveillence[monthly_agg$month >= '2013-06-01'] <- 'after'
monthly_agg$surveillence[monthly_agg$month >= '2014-12-3'] <- 'after_after'
model <- lm(views ~ month + surveillence + month*surveillence, data = monthly_agg)
summary(model)
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = monthly_agg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -261116  -60090   -3068   74682  242163
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    1.344e+07  2.212e+06   6.078 1.28e-07 ***
## month                         -8.068e+02  1.371e+02  -5.884 2.61e-07 ***
## surveillenceafter_after       -7.257e+06  5.632e+06  -1.289    0.203
## surveillencebefore            -1.230e+07  2.453e+06  -5.014 6.11e-06 ***
## month:surveillenceafter_after  4.577e+02  3.410e+02   1.342    0.185
## month:surveillencebefore       7.778e+02  1.535e+02   5.068 5.04e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 99590 on 54 degrees of freedom
## Multiple R-squared:  0.7424, Adjusted R-squared:  0.7186
## F-statistic: 31.13 on 5 and 54 DF,  p-value: 9.146e-15
```

```r
monthly_agg$prediction <- predict(model, monthly_agg)
monthly_agg$se <- predict(model, monthly_agg,
                      se.fit = TRUE)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
monthly_agg$LoCI <- monthly_agg$prediction - z.val * monthly_agg$se
monthly_agg$HiCI <- monthly_agg$prediction + z.val * monthly_agg$se
monthly_agg$month <- ymd(monthly_agg$month)
ggplot(monthly_agg,
       aes(x = month,
           y = prediction)) +
  geom_smooth(aes(ymin = LoCI,
                  ymax = HiCI,
                  color = surveillence),
              stat = "identity") +
  geom_point(data = monthly_agg, aes(x=month, y = views)) +
  geom_vline(xintercept = as.Date('2013-06-01'), linetype = 2, colour = 'blue') +
  geom_vline(xintercept = as.Date('2014-12-3'), linetype = 2, colour = 'blue') +
  ylab('Views') +
  xlab('Time (monthly)') +
  scale_x_date(date_breaks = "6 month", labels = date_format("%Y-%b")) +
   theme_bw(base_size = 5) +
  scale_y_continuous(labels = comma)
```

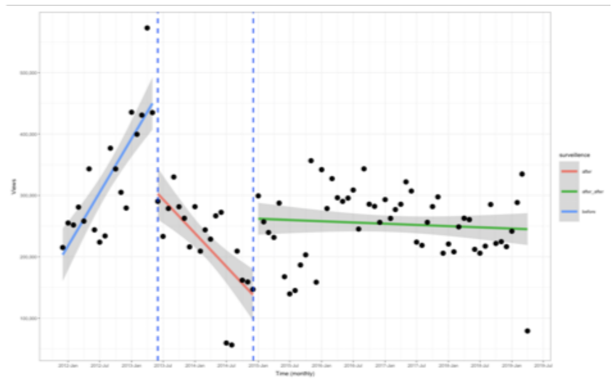
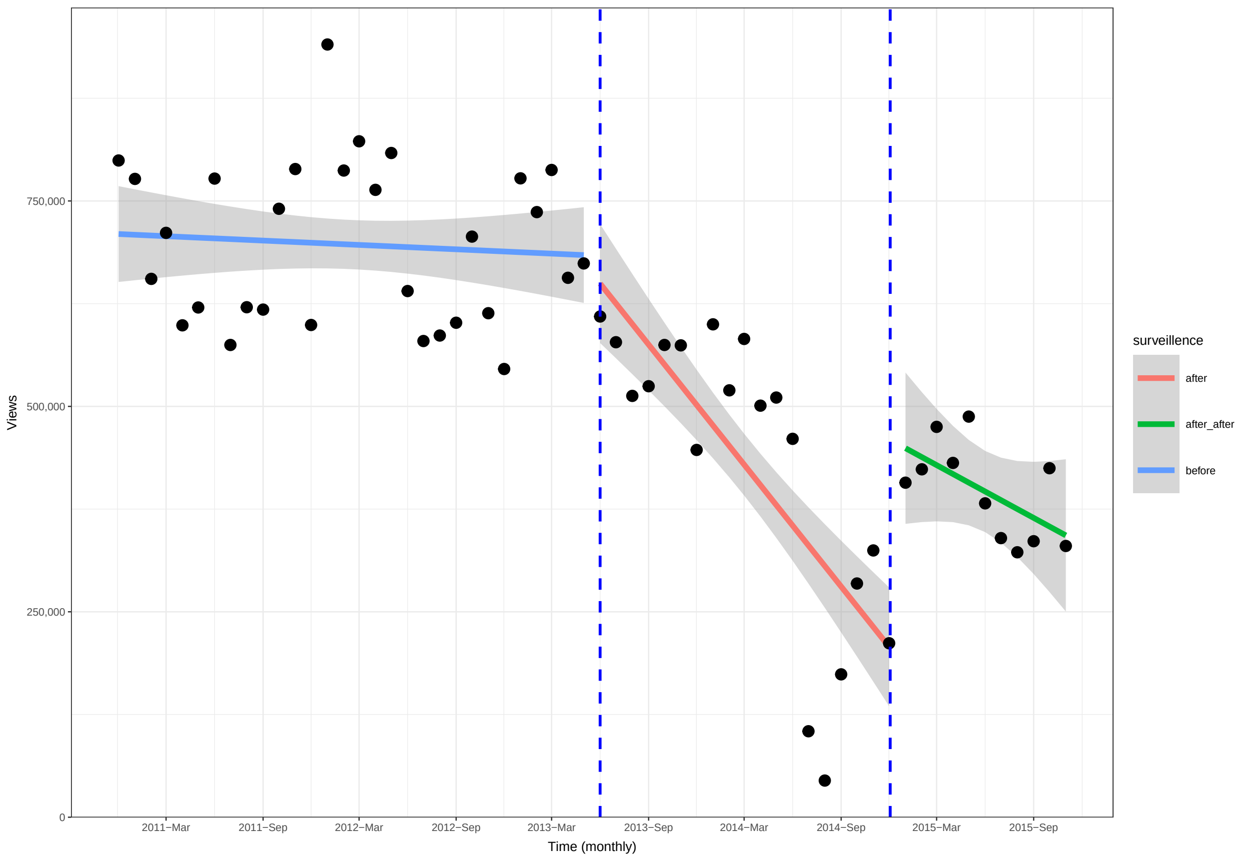


Figure 7: Original Graph with full data



The graph below shows that there is stable trend after January 2015. This graph shows that view after 2015 is higher than from 2013 to 2015. This is only graph that may support author's claim that there had been a trend recovery, and trend stays constant. However, the data is not segmented in equal time bins. This made our group explore further in equal time segmetents of trends after 2015, in the following works below.

```
monthly_agg <- terrorism_data_long %>%
  group_by(month=floor_date(date, "month")) %>%
  summarize(views=sum(views))
monthly_agg$surveillence <- 'before'
monthly_agg$surveillence[monthly_agg$month >= '2013-06-01'] <- 'after'
monthly_agg$surveillence[monthly_agg$month >= '2014-12-3'] <- 'after_after'
```

```r
monthly_agg$surveillence[monthly_agg$month >= '2016-06-3'] <- 'after_after_after'
monthly_agg$surveillence[monthly_agg$month >= '2016-06-3'] <- 'after_after_after_after'
model <- lm(views ~ month + surveillence + month*surveillence, data = monthly_agg)
summary(model)
```

```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = monthly_agg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -261116  -60090   -3068   74682  242163
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     1.344e+07  2.212e+06   6.078 1.28e-07 ***
## month                          -8.068e+02  1.371e+02  -5.884 2.61e-07 ***
## surveillenceafter_after        -7.257e+06  5.632e+06  -1.289    0.203
## surveillencebefore             -1.230e+07  2.453e+06  -5.014 6.11e-06 ***
## month:surveillenceafter_after   4.577e+02  3.410e+02   1.342    0.185
## month:surveillencebefore        7.778e+02  1.535e+02   5.068 5.04e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 99590 on 54 degrees of freedom
## Multiple R-squared:  0.7424, Adjusted R-squared:  0.7186
## F-statistic: 31.13 on 5 and 54 DF,  p-value: 9.146e-15
```

```r
monthly_agg$prediction <- predict(model, monthly_agg)
monthly_agg$se <- predict(model, monthly_agg,
                    se.fit = TRUE)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
monthly_agg$LoCI <- monthly_agg$prediction - z.val * monthly_agg$se
monthly_agg$HiCI <- monthly_agg$prediction + z.val * monthly_agg$se
monthly_agg$month <- ymd(monthly_agg$month)
ggplot(monthly_agg,
       aes(x = month,
           y = prediction)) +
  geom_smooth(aes(ymin = LoCI,
                ymax = HiCI,
                color = surveillence),
            stat = "identity") +
  geom_point(data = monthly_agg, aes(x=month, y = views)) +
  geom_vline(xintercept = as.Date('2013-06-01'), linetype = 2, colour = 'blue') +
  geom_vline(xintercept = as.Date('2014-12-3'), linetype = 2, colour = 'blue') +
  geom_vline(xintercept = as.Date('2016-06-3'), linetype = 2, colour = 'blue') +
  geom_vline(xintercept = as.Date('2016-06-3'), linetype = 2, colour = 'blue') +
  ylab('Views') +
  xlab('Time (monthly)') +
  scale_x_date(date_breaks = "6 month", labels = date_format("%Y-%b")) +
   theme_bw(base_size = 5) +
  scale_y_continuous(labels = comma)
```

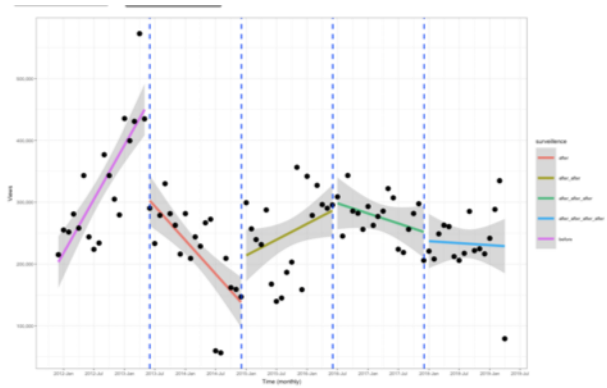
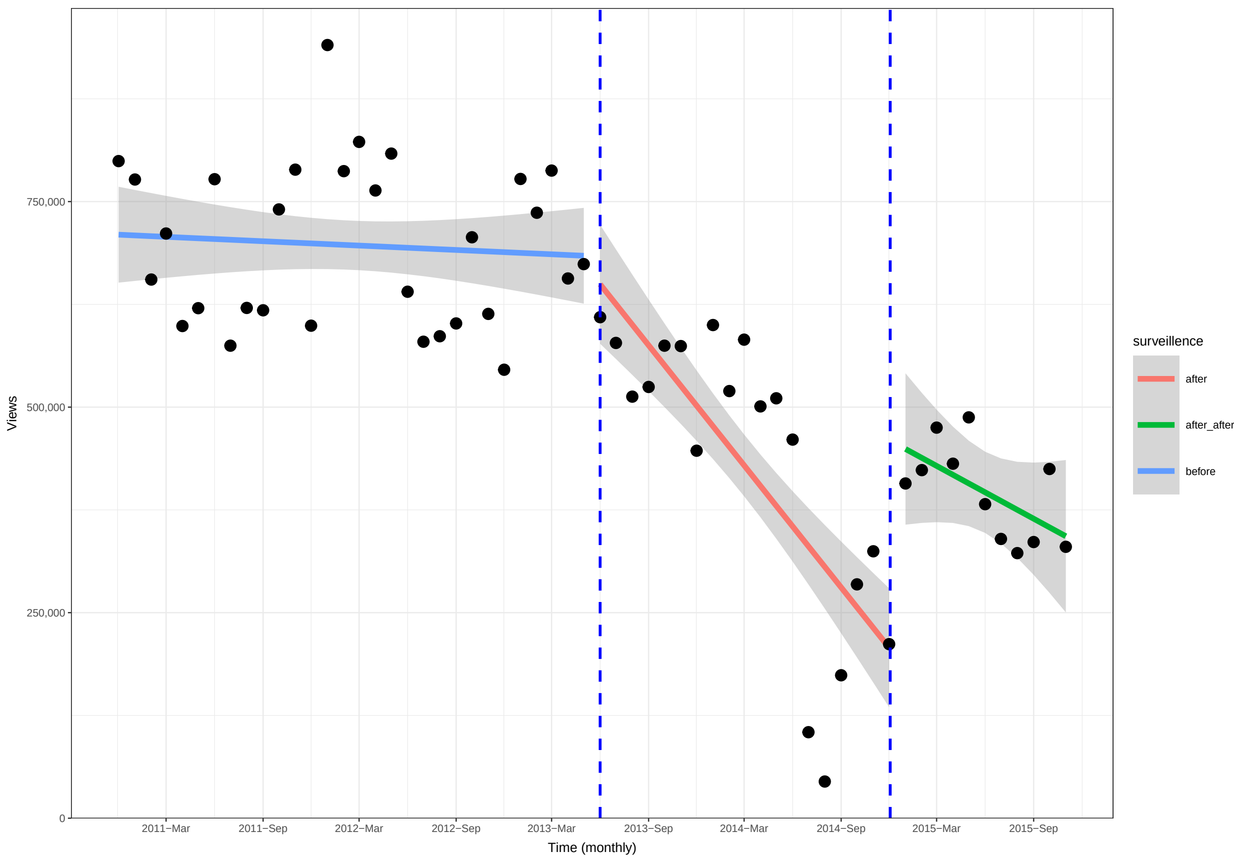


Figure 8: Original Segmented plot with full data



Now, our group had seperated the data into equal segments. The graph above shows trend recovery from Jan 2015 to July 2016, trend decrease from July 2016 to Jan 2018, then a stable trend from Jan 2018 to July 2019. This fluctuations may again raise question to paper's author's claim that there exists chilling effect due to Snowden Revelation.

3.2 Per-keyword Analysis

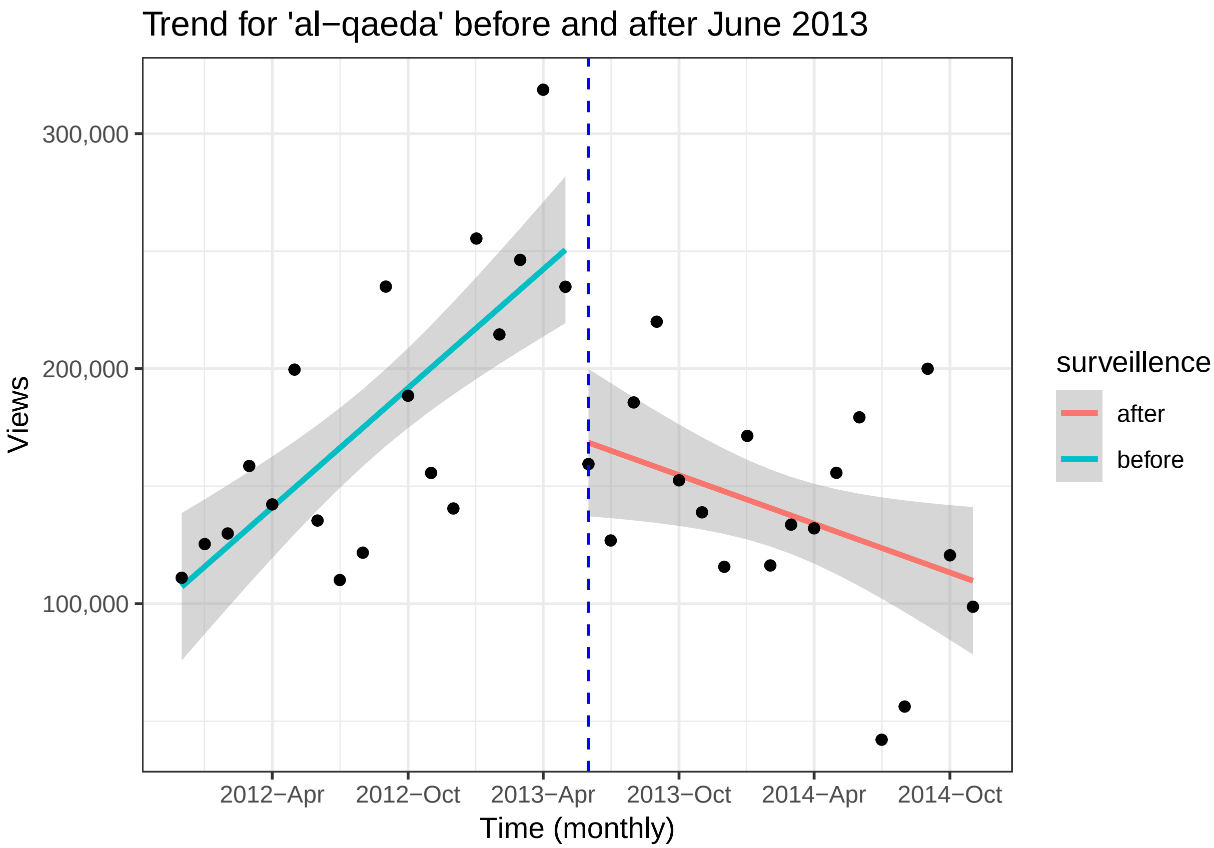
```
lm_plot_keyword <- function(input_df, article_name, gg_title){

df <- data.frame(input_df)
```

```r
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)$se.fit
z.val <- qnorm(1 - (1 - 0.90)/2)
df$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 ***
```

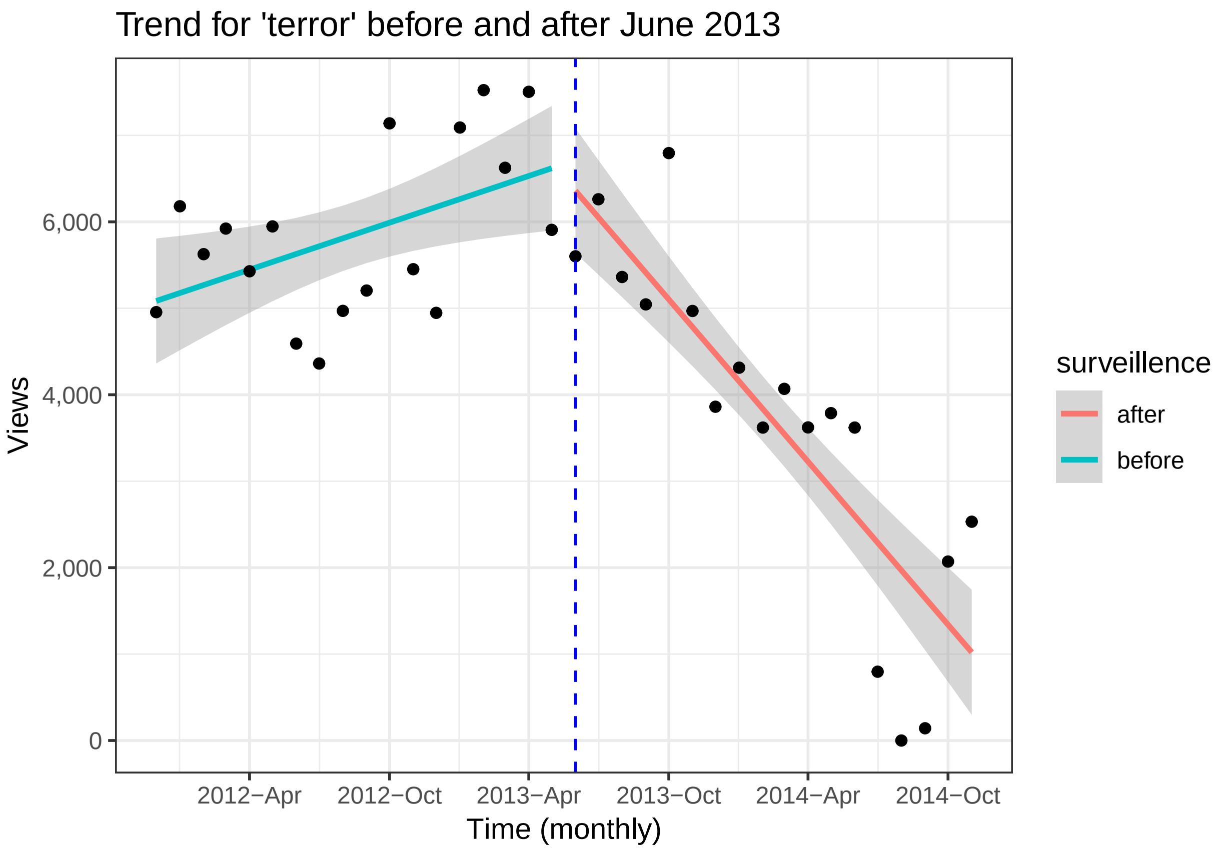
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 42080 on 32 degrees of freedom
## Multiple R-squared:  0.4909, Adjusted R-squared:  0.4432
## F-statistic: 10.29 on 3 and 32 DF,  p-value: 6.776e-05
```




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

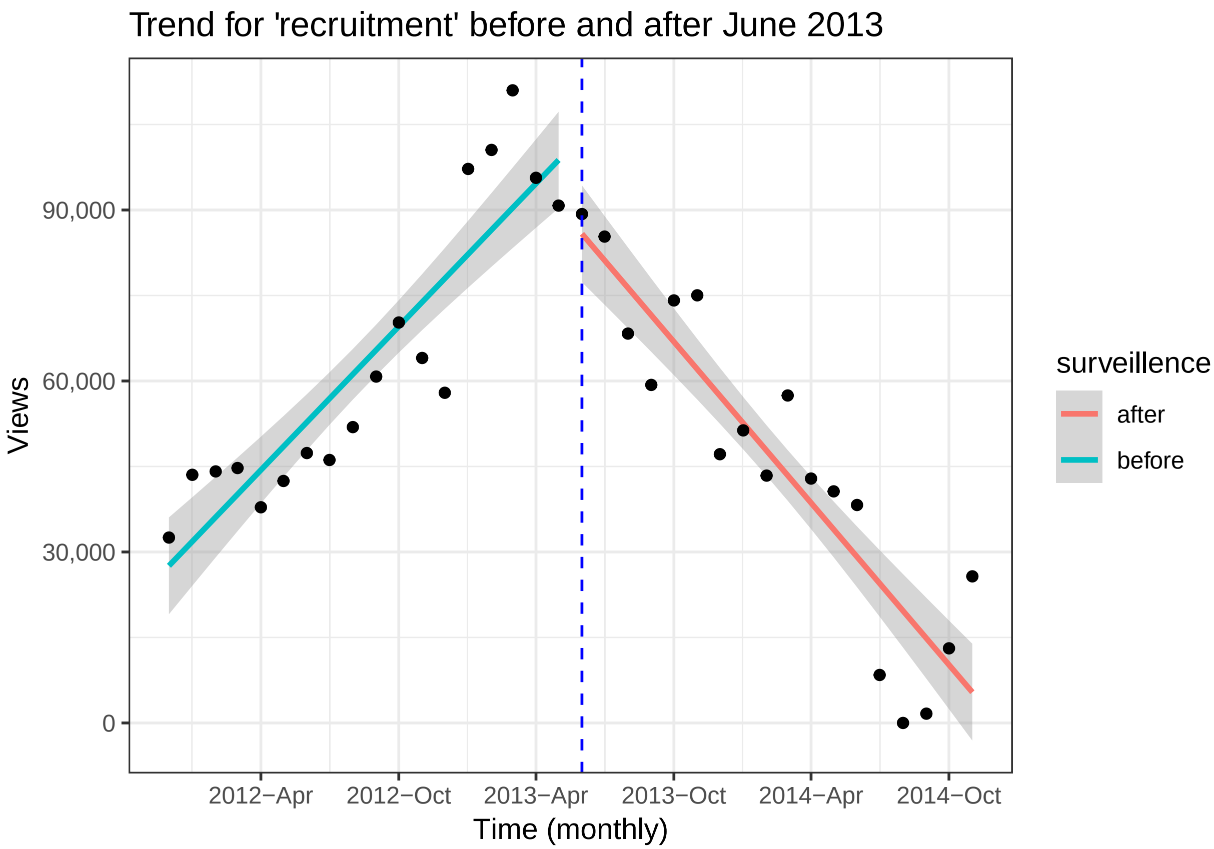
```
##
## Call:
## lm(formula = views ~ month + surveillence + month * surveillence,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1969.2  -700.2   172.0   754.2  1692.1
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                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
```




```
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

4. Summary

In our longer trend analysis, our group had found that trend fluctuations shown in polynomial fit graphs (n=4,5) show that there the chilling effect in 2013 may have been caused due to other reasons rather than NSA paranoia. When our group had seperated the data into equal time segments. The graph shows trend recovery from Jan 2015 to July 2016, trend decrease from July 2016 to Jan 2018, then a stable trend from Jan 2018 to July 2019. Again, this fluctuations raise concern to paper's author's claim that there exists chilling effect due to Snowden Revelation.

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

```
sessionInfo()
```

```
## R version 3.5.3 (2019-03-11)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS Mojave 10.14.3
##
## 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] igraph_1.2.4        here_0.1             wikipediatrend_2.1.1
##  [4] lubridate_1.7.4     forcats_0.3.0        stringr_1.4.0
##  [7] dplyr_0.8.0.1       purrr_0.3.0          readr_1.3.1
## [10] tidyr_0.8.2         tibble_2.1.1         ggplot2_3.1.1
## [13] tidyverse_1.2.1     scales_1.0.0
##
## loaded via a namespace (and not attached):
##  [1] tidyselect_0.2.5 xfun_0.4         haven_2.0.0      lattice_0.20-38
##  [5] colorspace_1.4-1 generics_0.0.2   htmltools_0.3.6  yaml_2.2.0
##  [9] rlang_0.3.4      pillar_1.3.1     glue_1.3.1       withr_2.1.2
## [13] hellno_0.0.1     modelr_0.1.3     readxl_1.3.0     plyr_1.8.4
## [17] munsell_0.5.0    gtable_0.3.0     cellranger_1.1.0 rvest_0.3.3
## [21] evaluate_0.13    labeling_0.3     knitr_1.21       broom_0.5.1
## [25] Rcpp_1.0.1       backports_1.1.3  jsonlite_1.6     hms_0.4.2
## [29] digest_0.6.18    stringi_1.4.3    grid_3.5.3       rprojroot_1.3-2
## [33] cli_1.1.0        tools_3.5.3      magrittr_1.5     lazyeval_0.2.2
## [37] crayon_1.3.4     pkgconfig_2.0.2  xml2_1.2.0       assertthat_0.2.1
## [41] rmarkdown_1.11   httr_1.4.0       rstudioapi_0.9.0 R6_2.4.0
## [45] nlme_3.1-137     compiler_3.5.3
```