The Impact of the Niger-Delta Amnesty Program.

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Introduction

In August 2009, the Nigerian government agreed to pay amnesty to rebel and militia groups operating in the Niger-Delta Oil producing region. The Niger-Delta Amnesty Program (NDAP) aims to resolve the natural resource violence that cost the Nigerian approximately USD 23.7 billion (World Bank, 2012). This report is a data analysis of violence in the Niger-Delta region to understand how the policy impacted violence in the region. The report is an excerpt of the main research and goes through the data wrangling process, visualization and model estimation of violence before and after the amnesty policy was enacted.

First, we load the data on violence in Nigeria. The data is retrieved from the Armed Conflict Location and Event Dataset (ACLED) in Stata .dta format. Every entry in the dataset represents a violent incidence in Nigeria. I also load a dataset that contains all the local government areas in Nigeria. I use this to match and merge the ACLED violence dataset so LGAs without any report of violence can take a value of zero. The next line shows the name of the variables in the ACLED dataset and after that I display the first five rows of the dataset.

```
con_05_16<- read.dta13("2005-01-01-2016-12-31-Nigeria.dta")
lga_id<-read.dta13("old_lga_id.dta")
```

```
names(con_05_16)
```

```
##  [1] "data_id"          "iso"              "event_id_cnty"    "event_id_no_cnty"
##  [5] "event_date"       "year"             "time_precision"   "event_type"
##  [9] "sub_event_type"   "actor1"           "assoc_actor_1"    "inter1"
## [13] "actor2"           "assoc_actor_2"    "inter2"           "interaction"
## [17] "region"           "country"          "admin1"           "admin2"
## [21] "admin3"           "location"         "latitude"         "longitude"
## [25] "geo_precision"    "source"           "source_scale"     "notes"
## [29] "fatalities"       "timestamp"        "iso3"
```

```
head(con_05_16)
```

```
##   data_id iso event_id_cnty event_id_no_cnty event_date year time_precision
## 1 6358078 566       NIG9976             9976  31-Dec-16 2016              2
## 2 6357751 566       NIG9975             9975  31-Dec-16 2016              1
## 3 6358020 566       NIG9973             9973  30-Dec-16 2016              1
## 4 6313775 566       NIG9974             9974  30-Dec-16 2016              1
## 5 6357668 566       NIG9972             9972  30-Dec-16 2016              1
## 6 6313392 566       NIG9971             9971  29-Dec-16 2016              1
##                   event_type sub_event_type
## 1     Strategic developments        Arrests
## 2 Explosions/Remote violence   Suicide bomb
## 3                    Battles    Armed clash
## 4 Violence against civilians         Attack
## 5                    Battles    Armed clash
## 6 Violence against civilians         Attack
##                                                                           actor1
## 1                                               Military Forces of Nigeria (2015-)
## 2 Islamic State (West Africa) and/or Boko Haram - Jamatu Ahli is-Sunnah lid-Dawatai wal-Jihad
```

```
## 3                                                            Military Forces of Nigeria (2015-)
## 4                                                             Private Security Forces (Nigeria)
## 5                                                            Military Forces of Nigeria (2015-)
## 6                                                             Private Security Forces (Nigeria)
##   assoc_actor_1 inter1
## 1                    1
## 2                    2
## 3                    1
## 4                    8
## 5                    1
## 6                    8
##                                                                                          actor2
## 1 Islamic State (West Africa) and/or Boko Haram - Jamatu Ahli is-Sunnah lid-Dawatai wal-Jihad
## 2                                                                          Civilians (Nigeria)
## 3 Islamic State (West Africa) and/or Boko Haram - Jamatu Ahli is-Sunnah lid-Dawatai wal-Jihad
## 4                                                                          Civilians (Nigeria)
## 5 Islamic State (West Africa) and/or Boko Haram - Jamatu Ahli is-Sunnah lid-Dawatai wal-Jihad
## 6                                                                          Civilians (Nigeria)
##   assoc_actor_2 inter2 interaction         region country    admin1     admin2
## 1                    2          12 Western Africa Nigeria     Borno      Gwoza
## 2                    7          27 Western Africa Nigeria     Borno  Maiduguri
## 3                    2          12 Western Africa Nigeria      Yobe   Damaturu
## 4                    7          78 Western Africa Nigeria Akwa Ibom        Itu
## 5                    2          12 Western Africa Nigeria     Borno Kala/Balge
## 6                    7          78 Western Africa Nigeria Akwa Ibom        Itu
##   admin3              location latitude longitude geo_precision
## 1     NA Sambisa Forest Reserve  11.2500   13.4167             2
## 2     NA             Maiduguri  11.8464   13.1603             1
## 3     NA              Damaturu  11.7470   11.9608             2
## 4     NA                   Oku   5.0475    7.9086             1
## 5     NA                  Rann  12.2829   14.4724             1
## 6     NA                   Oku   5.0475    7.9086             1
##               source source_scale
## 1 This Day (Nigeria)     National
## 2      Sun (Nigeria)     National
## 3 This Day (Nigeria)     National
## 4 This Day (Nigeria)     National
## 5   Sahara Reporters     Regional
## 6 This Day (Nigeria)     National
##
## 1
## 2
## 3
## 4 Sources said the armed mercenaries numbering more than 50 allegedly released by Ikot-Offiong villag
## 5
## 6 Sources said the armed mercenaries numbering more than 50 allegedly released by Ikot-Offiong villag
##   fatalities  timestamp iso3
## 1          0 1574121968  NGA
## 2          1 1574121967  NGA
## 3          1 1574121968  NGA
## 4          4 1572403784  NGA
## 5         15 1574121966  NGA
## 6          3 1572403784  NGA
```

```
head(lga_id)
```

```
##   state2            lgga lga
## 1   Abia        abanorth 101
## 2   Abia        abasouth 102
## 3   Abia       arochukwu 103
## 4   Abia           bende 104
## 5   Abia         ikwuano 105
## 6   Abia isialangwanorth 106
```

Next, I load the data set into a dplyr data frame and select only features that are important for the research. Afterwards, I generate a variable of ones for each observation reported in the dataset. The variable of ones will help identify where and when a violent event occurred - represented by 0, 1. The important features include the year the violence was recorded (year), the classification of the event (event_type), the name of violent actors (actor1, actor2), a grouping of the type of actors (inter1, inter2), the name of state and LGAs (admin1 and admin2 respectively), number of deaths reported (fatalities) and the variable of ones that represents each entry in ACLED.

```
con_data<-tbl_df(con_05_16)
con_data<-mutate(con_data, event=1)

con_data1<-dplyr::select(con_data, year, event_type, actor1, actor2, inter1, inter2, admin1, admin2, fa

head(con_data1)
```

I also generate variables to identify and represent the different classification of violence in the ACLED dataset. These variables include battle involving government forces (Battle), violence against civilians (VAC), protests (Protests) and Violence that involved rebel, ethnic and political militias (Rebel).

```
con_data1<-mutate(con_data1, Battles=0, VAC=0, Protests=0, Rebel=0)

con_data1$Battles[con_data1$event_type=="Battles"]<-1
con_data1$Protests<-with(con_data1, ifelse(event_type=="Protests", 1, Protests))
con_data1$VAC<-with(con_data1, ifelse(event_type=="Violence against civilians", 1, VAC))
con_data1$Rebel[con_data1$inter1==2 | con_data1$inter1==3 | con_data1$inter1==4]<-1
con_data1$Rebel[con_data1$inter2==2 | con_data1$inter2==3 | con_data1$inter2==4]<-1
```

I group the dataset by admin1 (State), admin2(LGA), year.

```
con_data1<-dplyr::select(con_data1, year, admin1, admin2, fatalities, event, Battles, VAC, Protests, Re
con_data1<-group_by(con_data1, admin1, admin2, year)
head(con_data1)
```

Based on the grouping variables, I sum the number of all classes of incidence.

```
con_ev_data<-summarise_at(con_data1, vars(fatalities, event, Battles, VAC, Protests, Rebel),
             funs(sum(., na.rm=T)))
head(con_ev_data)
```

```
## # A tibble: 6 x 9
## # Groups:   admin1, admin2 [1]
##   admin1 admin2     year fatalities event Battles   VAC Protests Rebel
##   <chr>  <chr>     <int>      <int> <dbl>   <dbl> <dbl>    <dbl> <dbl>
## 1 Abia   Aba South  2005          0     2       0     1        1     1
## 2 Abia   Aba South  2008          3     1       1     0        0     1
## 3 Abia   Aba South  2009         10     3       2     0        1     2
## 4 Abia   Aba South  2010          5     6       2     4        0     6
```

```
## 5 Abia   Aba South  2013          2     2       1     0        1     1
## 6 Abia   Aba South  2014          0     2       0     1        0     2
```

Next, I prepare the dataset to merge with the list of all LGAs in Nigeria.

```
con_ev_data$admin2<-tolower(con_ev_data$admin2)
con_ev_data$admin2<-gsub(" ", "", con_ev_data$admin2)
con_ev_data$admin2<-gsub("-", "", con_ev_data$admin2)
con_ev_data$admin2<-gsub("/", "", con_ev_data$admin2)
names(con_ev_data)[names(con_ev_data)=="admin1"]<-"state"
names(con_ev_data)[names(con_ev_data)=="admin2"]<-"lgga"

head(con_ev_data)
```

```
## # A tibble: 6 x 9
## # Groups:   state, lgga [1]
##   state lgga      year fatalities event Battles   VAC Protests Rebel
##   <chr> <chr>    <int>      <int> <dbl>   <dbl> <dbl>    <dbl> <dbl>
## 1 Abia  abasouth  2005          0     2       0     1        1     1
## 2 Abia  abasouth  2008          3     1       1     0        0     1
## 3 Abia  abasouth  2009         10     3       2     0        1     2
## 4 Abia  abasouth  2010          5     6       2     4        0     6
## 5 Abia  abasouth  2013          2     2       1     0        1     1
## 6 Abia  abasouth  2014          0     2       0     1        0     2
```

To ensure the two datasets merge correctly, I make sure the merge variables of state and LGAs are identical in the both dataset. I created a variable that returns "FALSE" when observations are not found in both dataset. With the TRUE/FALSE variable, I identify which naming of State and LGAs to change.

```
id_in_con<-unique(con_ev_data[c("state", "lgga")])
id_in_con$rename_lgga<-!id_in_con$lgga %in% lga_id$lgga
rename_lga<-filter(id_in_con, rename_lgga==TRUE)

head(rename_lga)
```

```
## # A tibble: 6 x 3
## # Groups:   state, lgga [6]
##   state   lgga         rename_lgga
##   <chr>   <chr>        <lgl>
## 1 Abia    isiukwuato   TRUE
## 2 Abia    osisiomangwa TRUE
## 3 Adamawa fufore       TRUE
## 4 Adamawa girei        TRUE
## 5 Bauchi  jama'are     TRUE
## 6 Bayelsa yenegoa      TRUE
```

```
con_ev_data$lgga[con_ev_data$lgga=="isiukwuato"]<-"isuikwuato"
con_ev_data$lgga<-gsub("osisiomangwa", "osisioma", con_ev_data$lgga)
con_ev_data$lgga<-gsub("fufore", "fufure", con_ev_data$lgga)
con_ev_data$lgga<-gsub("girei", "grie", con_ev_data$lgga)
con_ev_data$lgga<-gsub("jama'are", "jamaare", con_ev_data$lgga)
con_ev_data$lgga<-gsub("yenegoa", "yenagoa", con_ev_data$lgga)
con_ev_data$lgga<-gsub("bekwara", "bekwarra", con_ev_data$lgga)
con_ev_data$lgga<-gsub("yakurr", "yakuur", con_ev_data$lgga)
con_ev_data$lgga<-gsub("aiyekire(gbonyin)", "gbonyin", con_ev_data$lgga)
con_ev_data$lgga[con_ev_data$lgga=="aiyekire(gbonyin)"]<-"gbonyin"
con_ev_data$lgga<-gsub("abujamunicipal", "municipalareacouncil", con_ev_data$lgga)
```

```
con_ev_data$lgga<-gsub("birnikudu", "birninkudu", con_ev_data$lgga)
con_ev_data$lgga<-gsub("jema'a", "jemaa", con_ev_data$lgga)
con_ev_data$lgga<-gsub("markafi", "makarfi", con_ev_data$lgga)
con_ev_data$lgga<-gsub("zangokataf", "zangonkataf", con_ev_data$lgga)
con_ev_data$lgga<-gsub("garummallam", "garunmallam", con_ev_data$lgga)
con_ev_data$lgga<-gsub("olamabolo", "olamaboro", con_ev_data$lgga)
con_ev_data$lgga<-gsub("ifakoijaye", "ifakoijaiye", con_ev_data$lgga)
con_ev_data$lgga<-gsub("nasarawaeggon", "nasarawaegon", con_ev_data$lgga)
con_ev_data$lgga<-gsub("aiyedade", "aiyedaade", con_ev_data$lgga)
con_ev_data$lgga<-gsub("atakumosaeast", "atakunmosaeast", con_ev_data$lgga)
con_ev_data$lgga<-gsub("ileshaeast", "ilesaeast", con_ev_data$lgga)
con_ev_data$lgga<-gsub("oyowest", "oyo", con_ev_data$lgga)
con_ev_data$lgga<-gsub("emohua", "emuoha", con_ev_data$lgga)
con_ev_data$lgga<-gsub("obiaakpor", "obioakpor", con_ev_data$lgga)
con_ev_data$lgga<-gsub("karinlamido", "karimlamido", con_ev_data$lgga)
con_ev_data$lgga<-gsub("kurmi", "kumi", con_ev_data$lgga)
con_ev_data$lgga<-gsub("tarmua", "tarmuwa", con_ev_data$lgga)
con_ev_data$lgga<-gsub("birninmagaji", "birninmagajikiyaw", con_ev_data$lgga)
con_ev_data$lgga<-gsub("tsafe", "chafe", con_ev_data$lgga)
```

I re-run the test and now both state and LGA variable are identical in both datasets.

```
id_in_con2<-unique(con_ev_data[c("state", "lgga")])
id_in_con2$rename_lgga<-!id_in_con2$lgga %in% lga_id$lgga
filter(id_in_con2, rename_lgga==TRUE)
```

```
## # A tibble: 0 x 3
## # Groups:   state, lgga [0]
## # ... with 3 variables: state <chr>, lgga <chr>, rename_lgga <lgl>
```

For the data analysis, I will need data from 2005 to 2016 year time period that contains almost the same number of observations before and after the amnesty policy was enacted. I create a dplyr dataframe of the LGAs and expand the data of 774 LGAs over 9 year period giving a total of 9288 observations.

```
nig_lgga<-tbl_df(lga_id)
nig_lgga<-expandRows(nig_lgga, 12, count.is.col = F)
nig_lgga<-group_by(nig_lgga, state2, lgga)
names(nig_lgga)[names(nig_lgga)=='state2'] <- 'state'

nig_lgga<-mutate(nig_lgga, year=(seq("2005", "2016", 1)))
dim(nig_lgga)
```

```
## [1] 9288    4
```

The ACLED event dataset and the dataset representing all LGAs and state in Nigeria are merged. The observations in the merged dataset that have NA are those observations where there are no record of violence recorded by ACLED in the time period covered in the research.

```
####MERGING THE TWO DATASETS ###########
con_main<-merge(nig_lgga, con_ev_data, by=c("lgga", "year"), all.x = T)
head(con_main)
```

```
##     lgga year state.x lga state.y fatalities event Battles VAC Protests Rebel
## 1 abadam 2005   Borno 801    <NA>         NA    NA      NA  NA       NA    NA
## 2 abadam 2006   Borno 801    <NA>         NA    NA      NA  NA       NA    NA
## 3 abadam 2007   Borno 801    <NA>         NA    NA      NA  NA       NA    NA
## 4 abadam 2008   Borno 801    <NA>         NA    NA      NA  NA       NA    NA
```

```
## 5 abadam 2009   Borno 801    <NA>          NA     NA       NA  NA        NA     NA
## 6 abadam 2010   Borno 801    <NA>          NA     NA       NA  NA        NA     NA
```

Next, I replace NAs with zero values, create a variable that accounts for the years the amnesty policy was active (amnes_yr), and an indicator variable that identify Niger-Delta states in Nigeria.

```
con_main[is.na(con_main)]<-0
con_main$amnes_yr<-0
con_main$amnes_yr[con_main$year>=2010]<-1
con_main$niger_del_all<-0
con_main$niger_del_all[con_main$state.x=="Akwa" | con_main$state.x=="Bayelsa"
                   | con_main$state.x=="Edo" | con_main$state.x=="Rivers"
                   | con_main$state.x=="Cross" | con_main$state.x=="Delta"]<-1
names(con_main)
```

```
##  [1] "lgga"          "year"          "state.x"       "lga"
##  [5] "state.y"       "fatalities"    "event"         "Battles"
##  [9] "VAC"           "Protests"      "Rebel"         "amnes_yr"
## [13] "niger_del_all"
```

```
head(con_main)
```

```
##     lgga year state.x lga state.y fatalities event Battles VAC Protests Rebel
## 1 abadam 2005   Borno 801       0          0     0       0   0        0     0
## 2 abadam 2006   Borno 801       0          0     0       0   0        0     0
## 3 abadam 2007   Borno 801       0          0     0       0   0        0     0
## 4 abadam 2008   Borno 801       0          0     0       0   0        0     0
## 5 abadam 2009   Borno 801       0          0     0       0   0        0     0
## 6 abadam 2010   Borno 801       0          0     0       0   0        0     0
##   amnes_yr niger_del_all
## 1        0             0
## 2        0             0
## 3        0             0
## 4        0             0
## 5        0             0
## 6        1             0
```

Because I am interesting in the probability of having a violent event before and after the amnesty policy, I generate dummy varaibles that take a value of 1 if there was a reported incidence of violence by ACLED.

```
con_main$prob_rebel<-0
con_main$prob_rebel[con_main$Rebel>0]<-1

con_main$prob_Battles<-0
con_main$prob_Battles[con_main$Battles>0]<-1

con_main$prob_VAC<-0
con_main$prob_VAC[con_main$VAC>0]<-1

con_main$prob_event<-0
con_main$prob_event[con_main$event>0]<-1

con_main$prob_fatalities<-0
con_main$prob_fatalities[con_main$fatalities>0]<-1

con_main$prob_protest<-0
con_main$prob_protest[con_main$Protests>0]<-1
```

```r
names(con_main)
```

```
##  [1] "lgga"            "year"            "state.x"         "lga"
##  [5] "state.y"         "fatalities"      "event"           "Battles"
##  [9] "VAC"             "Protests"        "Rebel"           "amnes_yr"
## [13] "niger_del_all"   "prob_rebel"      "prob_Battles"    "prob_VAC"
## [17] "prob_event"      "prob_fatalities" "prob_protest"
```

```r
tail(con_main[c("lgga", "year", "prob_rebel", "prob_Battles", "prob_VAC", "prob_fatalities", "prob_prot
```

```
##      lgga year prob_rebel prob_Battles prob_VAC prob_fatalities prob_protest
## 9287 zuru 2011          0            0        0               0            0
## 9288 zuru 2012          0            0        0               0            0
## 9289 zuru 2013          0            0        0               0            0
## 9290 zuru 2014          0            1        0               1            0
## 9291 zuru 2015          0            0        0               0            0
## 9292 zuru 2016          1            1        0               1            0
```

The next step will be to specifically identify LGAs with oil fields in teh Nigeria. To do this, I use a dataset retrieved by Koos and Pierskalla (2016) complied by GIS solutions Nigeria.

```r
koos_oil_data<-read.dta13("oil_koos_2.dta")
names(koos_oil_data)
```

```
##  [1] "state"           "lgaa"            "flare_count"     "oilf_count"
##  [5] "electricity_pct" "ethnic_n"        "allocpc"         "pipearea"
##  [9] "state2"          "lgga"            "lga"
```

```r
head(koos_oil_data)
```

```
##   state              lgaa flare_count oilf_count electricity_pct ethnic_n
## 1  Abia         Aba North           0          0             75%        1
## 2  Abia         Aba South           0          0             71%        1
## 3  Abia          Arochukw           0          0             26%        2
## 4  Abia             Bende           0          0              7%        2
## 5  Abia           Ikwuano           0          0             22%        1
## 6  Abia Isiala Ngwa North           0          0             37%        2
##      allocpc    pipearea state2            lgga             lga
## 1 0.01773979 0.148888886   Abia        abanorth        abanorth
## 2 0.00953947 0.228431374   Abia        abasouth        abasouth
## 3 0.01407655 0.000000000   Abia       arochukwu       arochukwu
## 4 0.01313669 0.007298188   Abia           bende           bende
## 5 0.01650660 0.000000000   Abia         ikwuano         ikwuano
## 6 0.01548092 0.041607842   Abia isialangwanorth isialangwanorth
```

I merge the oil field location dataset with the main violence dataset using LGA names availble in both dataset. I generate a dummy variable for the presence of oil field across LGAs in Nigeria.

```r
con_main<-merge(con_main, koos_oil_data, by="lgga", all.x = T)
con_main<-dplyr::select(con_main, -c("lga.x", "state.y", "lgaa", "state", "lga.y"))

con_main$niger_del_oilf <- 0
con_main$niger_del_oilf[con_main$oilf_count>0 & con_main$niger_del_all==1] <- 1
names(con_main)
```

```
##  [1] "lgga"            "year"            "state.x"         "fatalities"
##  [5] "event"           "Battles"         "VAC"             "Protests"
```

```
##  [9] "Rebel"            "amnes_yr"         "niger_del_all"    "prob_rebel"
## [13] "prob_Battles"     "prob_VAC"         "prob_event"       "prob_fatalities"
## [17] "prob_protest"     "flare_count"      "oilf_count"       "electricity_pct"
## [21] "ethnic_n"         "allocpc"          "pipearea"         "state2"
## [25] "niger_del_oilf"
```

```
kable_styling(kable(table(dplyr::select(con_main[con_main$year==2010,], "niger_del_all", "niger_del_oil
  add_header_above(c(" ", "Oil Field" = 2)) %>%
  pack_rows("Niger-Delta", 1, 2)
```

	Oil Field	
	0	1
Niger-Delta		
0	651	0
1	68	55

The table above shows that of 774 LGAs, none of the LGAs located outside Niger-Delta have an oil field. All 55 LGAs with oil fields are located within the oil rich Niger-Delta region.

Mapping Niger-Delta Region in Nigeria.

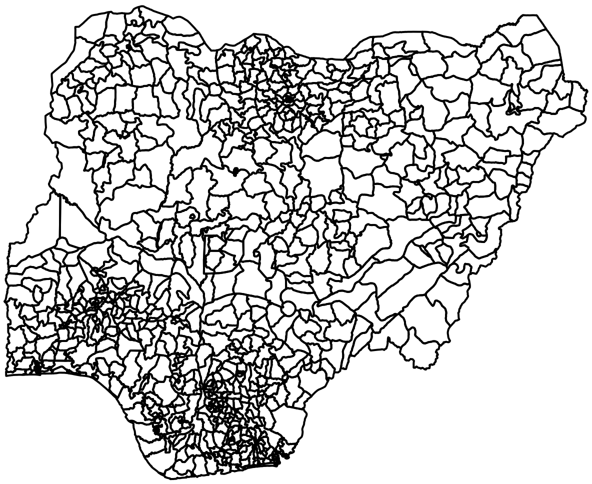
This research aims to understand how the amnesty policy changed impacted the incidence of violence in the oil producing region in Nigeria. In order to understand what local government areas we are comparing with oil producing Local government areas (LGAs), I will create a map of Nigeria representing LGAs in Niger-Delta with and without oil fields.

Firstly, I will load in a shape file that forms the base for the map in R using Rgdal package.

```
nig_lga4<-readOGR(dsn ="nga_adm",
                  layer="nga_admbnda_adm2_osgof_20170222")
```

```
## OGR data source with driver: ESRI Shapefile
## Source: "/Users/uzomailoanugo/Dropbox (Personal)/work_lodon/nga_adm", layer: "nga_admbnda_adm2_osgof_
## with 774 features
## It has 14 fields
```

```
plot(nig_lga4)
```



```r
head(nig_lga4$admin1Name)
```

```
## [1] Abia                      Abia
## [3] Federal Capital Territory Akwa Ibom
## [5] Ebonyi                    Ogun
## 37 Levels: Abia Adamawa Akwa Ibom Anambra Bauchi Bayelsa Benue ... Zamfara
```

```r
nig_lga4$admin1Name <- word(nig_lga4$admin1Name, 1)
head(nig_lga4$admin1Name)
```

```
## [1] "Abia"    "Abia"    "Federal" "Akwa"    "Ebonyi"  "Ogun"
```

In order to assign colour attributes that distinguish between LGAs in Niger-Delta from all other parts of Nigeria, I assign numbers to LGAs. Number 1 will represent all other parts of Nigeria while '2' will be assigned LGAs in Niger-Delta.

```r
nig_lga4@data$Col <- 1

nig_lga4$Col[nig_lga4$admin1Name=="Abia"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Akwa"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Bayelsa"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Cross"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Delta"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Edo"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Imo"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Ondo"] <- 2
nig_lga4$Col[nig_lga4$admin1Name=="Rivers"] <- 2
```

Next, I will bring in the data I intend to use for the analysis. The Koos and Pierskalla (2016) data identifies which LGAs in the Niger-Delta have oil fields. I will need this data to know which LGAs on the shape file to assigne a colour that indicates the presence of oil fields (red colour in this case).

```r
oil_lga1 <- unique(dplyr::select(con_main, "lgga", "state.x", "niger_del_oilf")) # I need only LGAs, St
oil_lga1 <- arrange(oil_lga1, state.x, lgga)
rownames(oil_lga1) <- 1:nrow(oil_lga1)
names(oil_lga1)[names(oil_lga1)=="lgga"]<- "admin2Name"


# A major part of this code is to ensure the LGA and State names on the dataset matches what is on the
nig_lga4$admin2Name <- tolower(nig_lga4$admin2Name)
nig_lga4$admin2Name <- gsub("-", "", nig_lga4$admin2Name)
nig_lga4$admin2Name <- gsub("/", "", nig_lga4$admin2Name)
nig_lga4$admin2Name <- gsub(" ", "", nig_lga4$admin2Name)

new_oil <-oil_lga1[oil_lga1$niger_del_oilf==1,] # subset and assign data that have oil field into a new
new_oil <- dplyr::tbl_df(new_oil)
new_oil <- dplyr::select(new_oil, admin2Name)

nig_lga4@data$oilf <- NA # Create a new attribute that will hold the colour assignment on the shape fil

# This loop assigns an integer (2) into the specific LGAs that have oil fields.
for (i in new_oil$admin2Name) {
        nig_lga4$oilf[nig_lga4$admin2Name== i] <- 2
}

oilf_col <- c(0,"brown")[nig_lga4$oilf] # I assign the colour brown to indicate oil fields
```

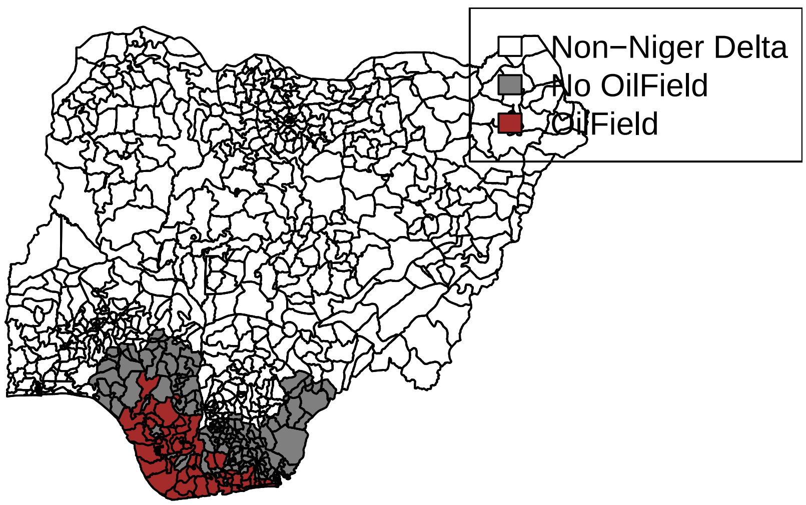
```
nd_colour <- c("white","grey50")[nig_lga4$Col] # I assign the colour grey to indicate the Niger-Delta r
```

I plot the maps, assigning colour that represents Non-Niger Delta, Niger-Delta without oil fields and Niger-Delta with oil fields.

```
plot(nig_lga4,
     col=nd_colour, main="Niger Delta Oil Producing Region")

plot(nig_lga4,
     col=nd_colour, main="Niger Delta Oil Producing Region")
plot(nig_lga4,
     col=oilf_col, add = T)
legend("topright", legend = c("Non-Niger Delta", "No OilField", "OilField"),
       fill = c('white', 'grey50', 'brown'))
```

Niger Delta Oil Producing Region



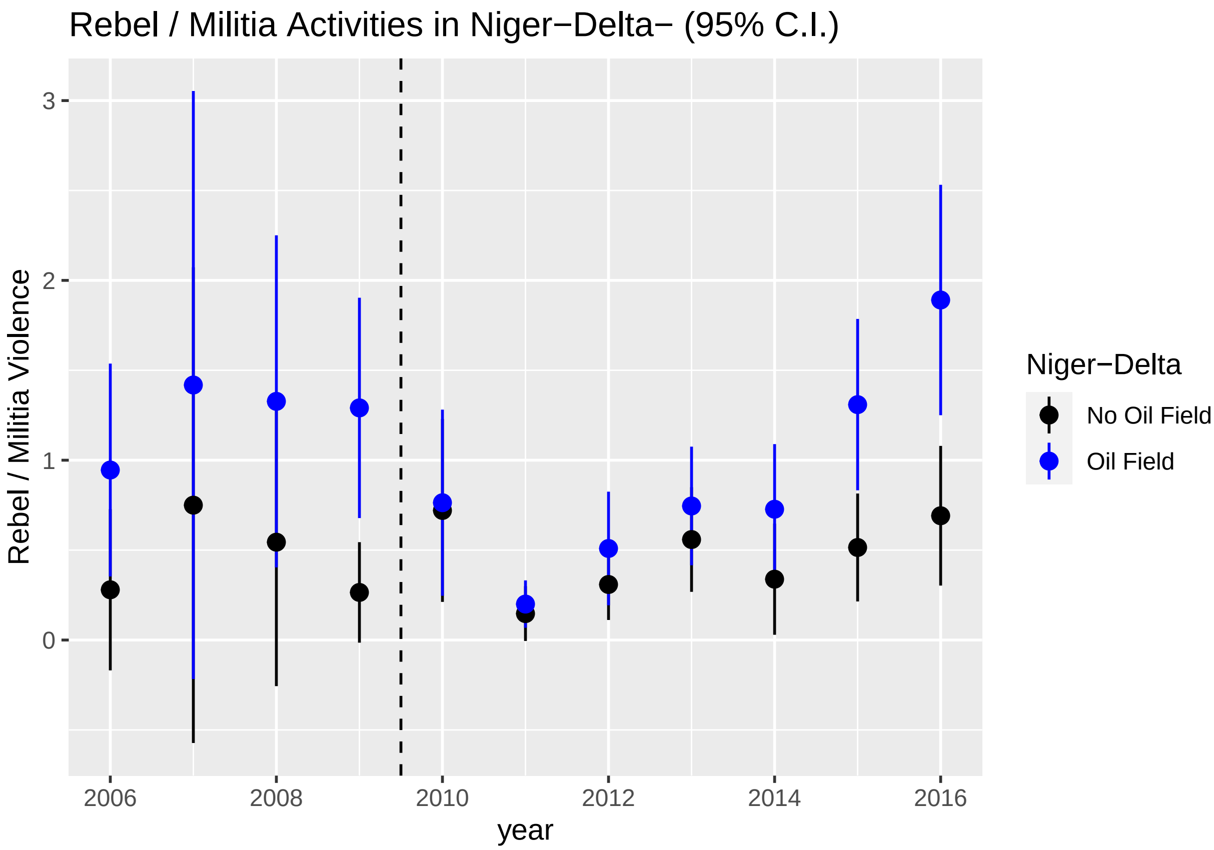
The map allows us to have a visual representation of Nigeria with the different types of LGAs. The coloured (Grey and Brown) area is the Niger-Delta region. The brown region are LGAs with oil fields in Nigeria. The research aims to compare the incidence of rebel and militia violence between Niger-Delta LGAs with and without oil fields before and after the amnesty policy was enacted.

Before we go into the parametric model for the estimation, it will be a good idea to see the trend in unconditional mean of rebel/militia events in the data. I create a subset of the of events in the Niger-Delta and transform the oil field dummy variable as factor to aid in plotting.

```
con_mean<-con_main[con_main$niger_del_all==1 & con_main$year>2005,]
con_mean$niger_del_oilf<-as.factor(con_mean$niger_del_oilf)
```

The plot of unconditional means of rebel/militia event using ggplot2.

```
ggplot(data = con_mean, aes(x = year, y = Rebel, group = niger_del_oilf, colour = niger_del_oilf)) +
  #geom_point(size = 4, alpha = .5) + # always plot the raw data
  stat_summary(fun.data = "mean_cl_normal") +
  labs(title = "Rebel / Militia Activities in Niger-Delta- (95% C.I.)")+
  geom_vline(xintercept = 2009.5, linetype = 2) +
  scale_color_manual(values = c('1' = 'blue', '0' = 'black'), labels = c("No Oil Field", "Oil Field"))+
  labs(y="Rebel / Militia Violence", colour = "Niger-Delta")
```



What we see from the plot is that immediately after 2009 - when the policy was announced - the level of rebel and militia activities in LGAs oil fields reduces to the level of LGAs without oil fields. The plot gives the impression that the policy had an impact on violence in Niger-Delta with LGAs.

Regression Model

The estimation strategy I will use is a difference-in-differences estimation strategy. For the difference-in-difference estimation to identify the effect of the amnesty policy on violence, it must be that Niger-Delta LGAs with and without oil fields must be on parallel trends before the amnesty policy. This implies that all factors that affect violence must fall into two categories - time invariant factors that are group specific and time changing factors that are group invariant. In this document I will not show how and why these assumptions hold in the research context, but in my thesis, I go through all the robustness checks.

The regression model is as specified as -

$$Rebel_{lt} = \alpha_l + \delta_t + \beta_0 \boldsymbol{Policy_t} \times \boldsymbol{Oil_l} + \gamma_l t + \epsilon_l$$

The dependent variable is the occurrence of rebel and militia event in Niger-Delta LGA l, at time t. I include LGA and time fixed effect to control for unobserved heterogeneity across space and time. The main variable of interest is β_0 that is the interaction between a variable *policy* - that picks up time period when the policy was active - and dummy *oil* that indicate what LGAs in our dataset have oil fields.

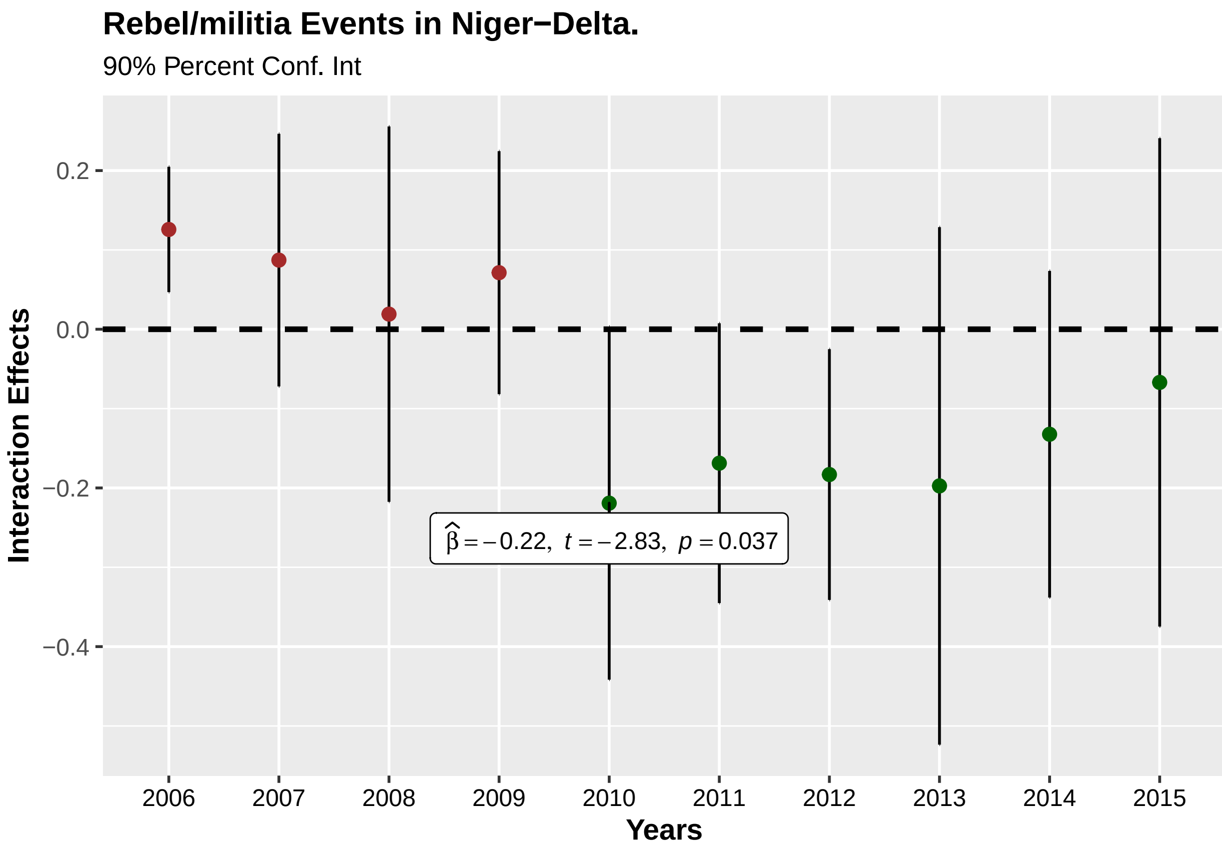
To check that my regression model does not violate the main parallel trend assumption, I conduct an event type study. The event type study allows us to see how violence in LGAs with and without oil fields in the Niger-Delta changed over time. We are interested in how the change differed immediate before and after the amnesty policy was enacted. That is, was the difference in violence between both types of LGAs relatively stable before amnesty, and was there a huge change in the difference immediately after the amnesty policy was issued. The command below runs the event study estimation and plots the regression coefficient.

```
con_felm_yrs_loop<-list(length(con_main[, 12:17]))
# Event study regression including interaction of oil field with year dummies for all conflict types.
for (i in seq_along(con_main[, 12:17])) {
  con_felm_yrs_loop[[i]]<-felm(con_main[, 12:17][[i]]~yr_2006:niger_del_oilf+
                               yr_2007:niger_del_oilf+
                               yr_2008:niger_del_oilf+
                               yr_2009:niger_del_oilf+
                               yr_2010:niger_del_oilf+
                               yr_2011:niger_del_oilf+
                               yr_2012:niger_del_oilf+
                               yr_2013:niger_del_oilf+
                               yr_2014:niger_del_oilf+
                               yr_2015:niger_del_oilf
                              | year:as.factor(lgga) + as.factor(year) + as.factor(lgga)| 0 | state.x,
                              data = con_main, subset = niger_del_all==1, exactDOF=TRUE, bootcluster=

  names(con_felm_yrs_loop)[[i]]<-names(con_main[, c(16, 30:34)])[[i]]
}

#Plot of the event study estimates.
ggcoefstats(con_felm_yrs_loop[[1]], only.significant = TRUE,
            point.args = list(size = 2, color = c("brown", "brown", "brown","brown", "darkgreen", "darkg
                                                 "darkgreen","darkgreen", "darkgreen", "darkgreen")),
            conf.level = 0.90,
            title = "Rebel/militia Events in Niger-Delta.",
            subtitle = "90% Percent Conf. Int",
            stats.labels = T,
            ggtheme = ggplot2::theme_gray()) +
  ggplot2::scale_y_discrete(labels = c("2006", "2007", "2008", "2009", "2010", "2011", "2012",
                                       "2013", "2014", "2015")) +
  ggplot2::labs(x="Interaction Effects", y="Years") +
  ggplot2::coord_flip()+
  theme(axis.text.x = element_text(color=c("black", "black", "black", "black", "black",
                                   "black", "black", "black", "black", "black")))
```

```
New names:
* NA -> ...1
* NA -> ...2
* NA -> ...3
* NA -> ...4
```



We see that the difference in the probability of violence is much higher in LGAs with oil field compared to LGAs without oil field relative to the base year of 2005 before the amnesty policy was enacted. We observe a sharp drop in the difference in probability of violence in LGAs with oil fields to LGAs without oil fields immediately after the amnesty policy was implemented. This provides evidence of a stable trend between types of LGAs before the amnesty policy and a sharp change in violence after the amnesty policy was implemented. Next, we look at average effects.

I create a list of dependent variable in my analysis. In addition to the probability of rebel activities, I also consider battles involving government forces, violence against civilians, protests and fatalities. Using the index of the desired dependent variables, I move the dependent variables into a list con_types.

```
con_types<-con_main[, 12:17]
names(con_types)
```

```
## [1] "prob_rebel"      "prob_Battles"    "prob_VAC"        "prob_event"
## [5] "prob_fatalities" "prob_protest"
```

Next I use the lfe package to create a regression model that loops through the dependent variable and collects results. Standard errors are clustered at state-level.

```
con_est_f<-list(length(con_types)) # Create a container for my regression results.

for (i in seq_along(con_types)) {
  con_est_f[[i]] <-felm(con_types[[i]]~niger_del_oilf:amnes_yr | year:as.factor(lgga) + as.factor(year)
}
```

I display the regression results using the stargazer package.

```
stargazer(con_est_f[[1]], con_est_f[[2]],con_est_f[[3]],con_est_f[[4]], con_est_f[[5]],con_est_f[[6]], 
          style = "aer", column.labels = c("Rebel", "All Events", "Battles", "Civilian Violence", "Fatal
```

```r
         covariate.labels = c("Policy Yr * Oil Field"),
         dep.var.caption = c("Conflict Violence"),
         dep.var.labels.include = F, nobs = T, align = TRUE)
```

```
Rebel and Militia Violence
===============================================================================================
                                Rebel   All Events Battles Civilian Violence Fatalities Protest
                                 (1)       (2)       (3)          (4)            (5)       (6)
-----------------------------------------------------------------------------------------------
Policy Yr * Oil Field          -0.349** -0.253***  -0.221*      -0.259**        -0.171     0.026
                               (0.105)   (0.063)   (0.086)      (0.100)        (0.101)   (0.065)

Observations                    1,476     1,476     1,476        1,476          1,476     1,476
R2                              0.464     0.376     0.438        0.516          0.408     0.422
Adjusted R2                     0.351     0.245     0.320        0.414          0.283     0.301
Residual Std. Error (df = 1218) 0.348     0.297     0.305        0.355          0.308     0.262
-----------------------------------------------------------------------------------------------
Notes:                         ***Significant at the 1 percent level.
                               **Significant at the 5 percent level.
                               *Significant at the 10 percent level.
```

The results indicate that after the amnesty policy was enacted, the probability of an incidence rebel and militia LGAs with oil fields decreased by 34.9 percent. We also see that the probability of battles involving government forces reduced by 22.1 percent and violence against civilians decreased by 25.9 percent. However, the amnesty policy had no effect on protest and fatalities in the oil producing region in the Niger-Delta.

Conclusion

The Niger-Delta amnesty program was implemented in 2010 to reduce the violence in the oil producing region of Nigeria. The estimation in this research quantifies the effect of the amnesty policy on violence in the Niger-Delta. We see that the amnesty policy reduced incidence of rebel and militia activities, battles involving governemnt forces and violent against civilians. However, the policy as expected had no effect on non-violent protest in the Niger-Delta.

The End