**Online Appendix**

**A1 – List of Countries Included in the CREV**

Afghanistan

Albania

Algeria

Angola

Armenia

Azerbaijan

Bahrain

Bangladesh

Belarus

Belgium

Bolivia

Bosnia-Herzegovina

Brazil

Bulgaria

Burundi

Cambodia

Chile

Columbia

Congo

Cote d’Ivorie

Croatia

Cuba

Czech Republic

Democratic Republic of the Congo

Democratic Republic of Vietnam

Ecuador

Egypt

El Salvador

Estonia

Ethiopia

Fiji

France

Georgia

Ghana

Guatemala

Guinea

Haiti

Honduras

India

Indonesia

Iran

Iraq

Israel

Jordan

Kazakhstan

Kenya

Kuwait

Kyrgyz Republic

Laos

Latvia

Lebanon

Liberia

Libya

Macedonia

Malawi

Malaysia

Mexico

Moldova

Mongolia

Morocco

Mozambique

Myanmar (Burma)

Namibia

Nepal

Nicaragua

Nigeria

North Korea

Pakistan

Panama

Papua New Guinea

Paraguay

Peru

Philippines

Poland

Romania

Russia

Rwanda

Senegal

Sierra Leone

Singapore

Slovakia

South Africa

South Korea

Sri Lanka

Sudan

Syria

Taiwan

Tajikistan

Tanzania

Thailand

Togo

Tunisia

Turkey

Turkmenistan

Uganda

Ukraine

Uzbekistan

Venezuela

Yemen

Zambia

Zimbabwe

**A2 CREV Codebook**

**Codebook for the Dataset of Countries at Risk for Electoral Violence (CREV)**

**Contents**

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Coding of the variables…2-3

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Other variables included in the dataset...4-6

How to cite this dataset:

[citation information removed for reviewing]

**Description of the Dataset**

The dataset of Countries at Risk of Electoral Violence (CREV) provides detailed dyadic information on electoral violence in 101 countries between1995 and 2013. For an election to be deemed “at risk” of electoral violence, two criteria have to be met. The country in which the election has taken place must not have been a fully consolidated democracy (defined as having a Polity IV (Marshall, Gurr and Jaggers 2016) score of 10) throughout the entire time period covered by the data, and it must have sufficient media coverage (defined as an average of at least 365 reported events per year in the ICEWS dataset (see below for details)). The dataset of Countries at Risk of Electoral Violence follows the National Elections across Democracy and Autocracy (NELDA) election classification (Hyde and Marinov 2012; 2014). Elections in CREV are for national-level legislative and executive contests only, local and regional elections are excluded, as are referendums and constituent assembly elections. Electoral violence is measured in a ten-month window around each election. We code violence beginning six months before the election, three months after the election, and the month of the election.

We provide two versions of the dataset. One is a time series cross-sectional (TSCS) dataset in which the unit of observation is the election, and where events of electoral violence are summed during the ten-month window. The other is a time series cross-sectional (TSCS) dataset in which the unit of observation is the electoral cycle month, and counts of violent events are specific to a given month during an electoral cycle. This codebook describes in detail the coding of both datasets. We also provide supplementary variables described in Section III. These variables are not counts of violence, but are instead variables from the NELDA dataset (Hyde and Marinov 2012), and other variables described below that are optional variables researchers can use if they want to construct weights for the data. We recommend weighting only the dataset of elections, and not the monthly dataset, as the number of media events recorded are aggregated yearly.

The data on electoral violence in CREV are based on the aggregation of violent events coded by the Integrated Crisis Early Warning System (ICEWS) automated event data coder developed by Lockheed Martin (Boschee et al. 2015). Electoral violence is defined as coercive force, directed towards electoral actors and/or objects, that occurs in the context of electoral competition. Data are taken from the ICEWS monadic aggregations data from 1995 to May 2014. The data originally contain information on electoral violence across 48 actor dyads, which we defined in more detail below. These 48 dyads are then aggregated into five different actor dyads for CREV. CREV measures two different kinds of electoral violence: verbal conflict, including threats made by one actor towards another, military build-ups targeting specific actors, and coercive violence falling short of actual bodily harm; and material conflict, including physical violence and assaults perpetrated by one actor against another. CREV contains information on electoral violence across five different actor dyads: any actor to an international actor, an international actor to any actor, nonstate actors to nonstate actors, nonstate actors to state actors, and state actors to nonstate actors. Further detail is provided below.

**Coding of the Variables**

In this section, we describe how CREV measures electoral violence. We describe the actors included in each of the five dyads described previously. We also describe in detail the definitions of violent events that are coded in each category of violence in CREV. Violent events are defined in CREV according to the Conflict and Mediation Event Observations (CAMEO) ontology. This is the standard coding ontology for automated event data. Below we describe the aggregation on CREV actor dyads from ICEWS actor dyads. We follow standards traditional in the literature when placing actors into CREV dyads.

1. **Dyads included in CREV and their ICEWS Aggregations**

* First Dyad: Any Actor to International Actor
  + ICEWS dyad(s) included in CREV dyad:
    - Government to International Organization
* Second Dyad: International Actor to Any Actor
  + ICEWS dyad(s) included in CREV Dyad:
    - International Organization towards Government
* Third Dyad: Nonstate Actors to Nonstate Actors
  + ICEWS dyad(s) included in CREV Dyad:
    - All Muslims towards Buddhists
    - All Muslims towards Christians
    - All Muslims towards Hindus
    - Buddhists towards all Muslims
    - Buddhists towards Christians
    - Buddhists towards Hindus
    - Christians towards all Muslims
    - Christians towards Buddhists
    - Christians towards Hindus
    - Hindus towards all Muslims
    - Hindus towards Buddhists
    - Hindus towards Christians
    - Ethnic actors towards religious actors
    - Ethnic actors towards separatists
    - Religious actors towards ethnic actors
    - Separatists towards ethnic actors
    - Dissidents towards Non Dissidents
    - Dissidents towards Dissidents
    - Opposition towards Ethnic Groups
* Fourth Dyad: Nonstate Actors to State Actors
  + ICEWS dyad(s) included in CREV dyad
    - All Muslims towards government
    - Buddhists towards government
    - Christians towards government
    - Communists towards government
    - Hindus towards government
    - Ethnic actors towards government
    - Ethnic actors towards parties
    - Opposition parties towards government
    - Opposition parties towards government parties
    - Opposition towards the country in general (national sectors)
    - Opposition towards Judicial Actors
    - Separatists towards national sectors
    - Separatists towards national sectors and government
    - Separatists towards government
    - Dissidents towards government
    - Dissident Opposition towards national sectors
    - Dissident Opposition towards military
* Fifth Dyad: State to Nonstate Actors
  + ICEWS dyad(s) included:
    - Government to ethnic actors
    - Government to opposition
    - Government to separatists
    - Parties towards ethnic actors
    - Government towards Muslims
    - Government towards dissidents
    - Government to Buddhists
    - Government to Christians
    - Government to Communists
    - Government to Hindus
    - Government to Media

1. **CAMEO codes included to measure electoral violence**

The Conflict and Mediation Event Observations ontology is described in detail elsewhere (see the CAMEO codebook, Schrodt 2012). We provide a brief description of the CAMEO events we utilize to measure electoral violence here. CREV includes information on two types of electoral violence: Threats and Attacks. These types of violence are themselves aggregations of five separate CAMEO violence codes. We describe what CAMEO codes go into making up the CREV violence codes in this section. All CAMEO codes described below are measured for all five CREV actor dyads.

* CREV category of violence “Threats”
  + CAMEO codes 130-139: Threaten. Defined as “all threats, coercive or forceful warnings with serious potential repercussions.”
  + CAMEO codes 150-154: Exhibit Force Posture. Defined as “all military or police moves that fall short of the actual use of force.”
  + CAMEO codes 170-175: Coerce. Defined as, ““repression, violence against civilians, or their rights or properties.”
* CREV category of violence “Attacks”
  + CAMEO codes 180-186: Assault. Defined as, “use of unconventional forms of violence which do not require high levels of organization typical of state military establishments or conventional weaponry.”
  + CAMEO codes 190-196: Fight. Defined as, “all uses of conventional force and acts of war typically by organized armed groups.”

**III. Description of Other Variables**

1. **Election data**

* Country
  + Character string, with name of corresponding country
* Isouncode
  + 3 Number UN ISO Country Code. Taken from the ICEWS dataset
* Ccode
  + Correlates of War Country Code (Sarkees and Wayman, 2010)
* ElectionID
  + NELDA Election ID variable
* Mmdd
  + Numeric variable recording month and date when election took place
* Year
  + Variable indicating year in which election took place
* Numevnt
  + Numeric variable summing the number of events recorded in ICEWS event data (both positive and negative) for a given country in a given year. Can be used for constructing weights, if desired.
* Population
  + The population of a country, in millions. Taken from multiple sources including CIA World Fact Book (Central Intelligence Agency, 2017), Varieties of Democracy (Coppedge et al. 2016a; 2016b), Penn World Tables (Feenstra, Inklaar and Timmer, 2013; Penn World Tables, 2017), Quality of Government (Dahlberg et al., 2017).
* Concurrent
  + A dummy variable indicating if a presidential and legislative election were held concurrently (1) or not (0).

1. **Monthly data**

* Country
  + Character string, with name of corresponding country
* Isouncode
  + 3 Number UN ISO Country Code. Taken from the ICEWS dataset
* Ccode
  + Correlates of War Country Code
* ElectionID
  + NELDA Election ID variable
* Mmdd
  + Numeric variable recording month and date when election took place
* Year.Month
  + Variable indicating year and month (in relation to election month) in which election took place
* Month
* Variable indicating month in which election took place; the month of the election is counted as ‘0’ and this variable is an integer ranging from -6 to 3 designating the data point in relation to election month
* Concurrent
  + A dummy variable indicating if a presidential and legislative election were held concurrently (1) or not (0).

1. **Weight**

* The weight variable is designed for users who wish to weight the event data by per capita media coverage. This weight is calculated by recording the total number of coded events in the ICEWS data in which the country conducting an election was the target country, then dividing this by the number of people living in the country (in millions). This variable is inverted and the mean is centered on 1, such that elections with less media coverage are weighted upwards, and elections in countries with more media coverage are weighted downwards.

**References**

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Schrodt, P. A. 2012. CAMEO: Conflict and Mediation Event Observations Event and Actor Codebook. *Pennsylvania State University*.

**A3: Code Used to Compile the Datasets**

setwd("C:/File Path")

library(plyr)

create\_typology\_year\_mnonth\_column<-function(y,m){

year.month<-paste(y,"-",m)

return (year.month)

}

get\_Any\_Intel\_Data<-function(combined\_df){

combined\_df<-data.frame(t(combined\_df),stringsAsFactors = F)

Typology\_Any\_Intl\_data2<-c(Any\_Intl\_Threats=0,Any\_Intl\_AttacksAssaults=0,Any\_Intl\_MassViolence=0)

# if(as.numeric(combined\_df$month) != 0){

combined\_CC<-as.numeric(matrix(combined\_df$COW.Code))

combined\_year\_month<-as.character(matrix(combined\_df$Year.Month))

Typology\_Any\_Intl\_data<-subset(Typology\_Any\_Intl,Typology\_Any\_Intl$COW.Code==combined\_CC & Typology\_Any\_Intl$Year.Month==combined\_year\_month)

Typology\_Any\_Intl\_data2<-c(Any\_Intl\_Threats=Typology\_Any\_Intl\_data$L1,Any\_Intl\_AttacksAssaults=Typology\_Any\_Intl\_data$L2,Any\_Intl\_MassViolence=Typology\_Any\_Intl\_data$L3)

#}

return(Typology\_Any\_Intl\_data2)

}

get\_Intel\_Any\_Data<-function(combined\_df){

combined\_df<-data.frame(t(combined\_df),stringsAsFactors = F)

Typology\_Intl\_Any\_data2<-c(Intl\_Any\_Threats=0,Intl\_Any\_AttacksAssaults=0,Intl\_Any\_MassViolence=0)

#if(as.numeric(combined\_df$month) != 0){

combined\_CC<-as.numeric(matrix(combined\_df$COW.Code))

combined\_year\_month<-as.character(matrix(combined\_df$Year.Month))

Typology\_Intl\_Any\_data<-subset(Typology\_Intl\_Any,Typology\_Intl\_Any$COW.Code==combined\_CC & Typology\_Intl\_Any$Year.Month==combined\_year\_month)

Typology\_Intl\_Any\_data2<-c(Intl\_Any\_Threats=Typology\_Intl\_Any\_data$L1,Intl\_Any\_AttacksAssaults=Typology\_Intl\_Any\_data$L2,Intl\_Any\_MassViolence=Typology\_Intl\_Any\_data$L3)

#}

return(Typology\_Intl\_Any\_data2)

}

get\_Nonstate\_Nonstate\_Data<-function(combined\_df){

combined\_df<-data.frame(t(combined\_df),stringsAsFactors = F)

Typology\_Nonstate\_Nonstate\_data2<-c(Nonstate\_Nonstate\_Threats=0,Nonstate\_Nonstate\_AttacksAssaults=0,Nonstate\_Nonstate\_MassViolence=0)

#if(as.numeric(combined\_df$month) != 0){

combined\_CC<-as.numeric(matrix(combined\_df$COW.Code))

combined\_year\_month<-as.character(matrix(combined\_df$Year.Month))

Typology\_Nonstate\_Nonstate\_data<-subset(Typology\_Nonstate\_Nonstate,Typology\_Nonstate\_Nonstate$COW.Code==combined\_CC & Typology\_Nonstate\_Nonstate$Year.Month==combined\_year\_month)

Typology\_Nonstate\_Nonstate\_data2<-c(Nonstate\_Nonstate\_Threats=Typology\_Nonstate\_Nonstate\_data$L1,Nonstate\_Nonstate\_AttacksAssaults=Typology\_Nonstate\_Nonstate\_data$L2,Nonstate\_Nonstate\_MassViolence=Typology\_Nonstate\_Nonstate\_data$L3)

#}

return(Typology\_Nonstate\_Nonstate\_data2)

}

get\_Nonstate\_state\_Data<-function(combined\_df){

combined\_df<-data.frame(t(combined\_df),stringsAsFactors = F)

Typology\_Nonstate\_state\_data2<-c(Nonstate\_state\_Threats=0,Nonstate\_state\_AttacksAssaults=0,Nonstate\_state\_MassViolence=0)

#if(as.numeric(combined\_df$month) != 0){

combined\_CC<-as.numeric(matrix(combined\_df$COW.Code))

combined\_year\_month<-as.character(matrix(combined\_df$Year.Month))

Typology\_Nonstate\_state\_data<-subset(Typology\_Nonstate\_State,Typology\_Nonstate\_State$COW.Code==combined\_CC & Typology\_Nonstate\_State$Year.Month==combined\_year\_month)

Typology\_Nonstate\_state\_data2<-c(Nonstate\_state\_Threats=Typology\_Nonstate\_state\_data$L1,Nonstate\_state\_AttacksAssaults=Typology\_Nonstate\_state\_data$L2,Nonstate\_state\_MassViolence=Typology\_Nonstate\_state\_data$L3)

#}

return(Typology\_Nonstate\_state\_data2)

}

get\_State\_Nonstate\_Data<-function(combined\_df){

combined\_df<-data.frame(t(combined\_df),stringsAsFactors = F)

Typology\_state\_Nonstate\_data2<-c(state\_Nonstate\_Threats=0,state\_Nonstate\_AttacksAssaults=0,state\_Nonstate\_MassViolence=0)

#if(as.numeric(combined\_df$month) != 0){

combined\_CC<-as.numeric(matrix(combined\_df$COW.Code))

combined\_year\_month<-as.character(matrix(combined\_df$Year.Month))

Typology\_state\_Nonstate\_data<-subset(Typology\_State\_Nonstate,Typology\_State\_Nonstate$COW.Code==combined\_CC & Typology\_State\_Nonstate$Year.Month==combined\_year\_month)

Typology\_state\_Nonstate\_data2<-c(state\_Nonstate\_Threats=Typology\_state\_Nonstate\_data$L1,state\_Nonstate\_AttacksAssaults=Typology\_state\_Nonstate\_data$L2,state\_Nonstate\_MassViolence=Typology\_state\_Nonstate\_data$L3)

#}

return(Typology\_state\_Nonstate\_data2)

}

get\_State\_State\_Data<-function(combined\_df){

combined\_df<-data.frame(t(combined\_df),stringsAsFactors = F)

Typology\_state\_state\_data2<-c(state\_state\_Threats=0,state\_state\_AttacksAssaults=0,state\_state\_MassViolence=0)

#if(as.numeric(combined\_df$month) != 0){

combined\_CC<-as.numeric(matrix(combined\_df$COW.Code))

combined\_year\_month<-as.character(matrix(combined\_df$Year.Month))

Typology\_state\_state\_data<-subset(Typology\_State\_State,Typology\_State\_State$COW.Code==combined\_CC & Typology\_State\_State$Year.Month==combined\_year\_month)

Typology\_state\_state\_data2<-c(state\_state\_Threats=Typology\_state\_state\_data$L1,state\_state\_AttacksAssaults=Typology\_state\_state\_data$L2,state\_state\_MassViolence=Typology\_state\_state\_data$L3)

#}

return(Typology\_state\_state\_data2)

}

Group\_Combined\_Data\_By\_ElectionID<-function(unique\_election\_ID){

combined\_data\_subset<-subset(combined\_dataSet\_final,combined\_dataSet\_final$ElectionID==unique\_election\_ID)

Any\_Intl\_Threats\_Sum<-colSums(matrix(unlist(combined\_data\_subset$Any\_Intl\_Threats)))

Any\_Intl\_AttacksAssaults\_sum<-colSums(matrix(unlist(combined\_data\_subset$Any\_Intl\_AttacksAssaults,sum)))

Any\_Intl\_MassViolence\_sum<-colSums(matrix(unlist(combined\_data\_subset$Any\_Intl\_MassViolence,sum)))

Intl\_Any\_Threats\_sum<-colSums(matrix(unlist(combined\_data\_subset$Intl\_Any\_Threats,sum)))

Intl\_Any\_AttacksAssaults\_sum<-colSums(matrix(unlist(combined\_data\_subset$Intl\_Any\_AttacksAssaults,sum)))

Intl\_Any\_MassViolence\_sum<-colSums(matrix(unlist(combined\_data\_subset$Intl\_Any\_MassViolence,sum)))

Nonstate\_Nonstate\_Threats\_sum<-colSums(matrix(unlist(combined\_data\_subset$Nonstate\_Nonstate\_Threats,sum)))

Nonstate\_Nonstate\_AttacksAssaults\_sum<-colSums(matrix(unlist(combined\_data\_subset$Nonstate\_Nonstate\_AttacksAssaults,sum)))

Nonstate\_Nonstate\_MassViolence\_sum<-colSums(matrix(unlist(combined\_data\_subset$Nonstate\_Nonstate\_MassViolence,sum)))

Nonstate\_state\_Threats\_sum<-colSums(matrix(unlist(combined\_data\_subset$Nonstate\_state\_Threats,sum)))

Nonstate\_state\_AttacksAssaults\_sum<-colSums(matrix(unlist(combined\_data\_subset$Nonstate\_state\_AttacksAssaults,sum)))

Nonstate\_state\_MassViolence\_sum<-colSums(matrix(unlist(combined\_data\_subset$Nonstate\_state\_MassViolence,sum)))

state\_Nonstate\_Threats\_sum<-colSums(matrix(unlist(combined\_data\_subset$state\_Nonstate\_Threats,sum)))

state\_Nonstate\_AttacksAssaults\_sum<-colSums(matrix(unlist(combined\_data\_subset$state\_Nonstate\_AttacksAssaults,sum)))

state\_Nonstate\_MassViolence\_sum<-colSums(matrix(unlist(combined\_data\_subset$state\_Nonstate\_MassViolence,sum)))

state\_state\_Threats\_sum<-colSums(matrix(unlist(combined\_data\_subset$state\_state\_Threats,sum)))

state\_state\_AttacksAssaults\_sum<-colSums(matrix(unlist(combined\_data\_subset$state\_state\_AttacksAssaults,sum)))

state\_state\_MassViolence\_sum<-colSums(matrix(unlist(combined\_data\_subset$state\_state\_MassViolence,sum)))

aggregated\_dataSet<-c(Country=combined\_data\_subset$Country.Name[1],ISO.UN.Code=combined\_data\_subset$UN.ISO.Code[1],

COW.Code=combined\_data\_subset$COW.Code[1],ElectionID=combined\_data\_subset$ElectionID[1],

Any\_Intl\_Threats=Any\_Intl\_Threats\_Sum,Any\_Intl\_AttacksAssaults=Any\_Intl\_AttacksAssaults\_sum,Any\_Intl\_MassViolence=Any\_Intl\_MassViolence\_sum,

Intl\_Any\_Threats=Intl\_Any\_Threats\_sum,Intl\_Any\_AttacksAssaults=Intl\_Any\_AttacksAssaults\_sum,Intl\_Any\_MassViolence\_MassViolence=Intl\_Any\_MassViolence\_sum,

Nonstate\_Nonstate\_Threats=Nonstate\_Nonstate\_Threats\_sum,Nonstate\_Nonstate\_AttacksAssaults=Nonstate\_Nonstate\_AttacksAssaults\_sum,Nonstate\_Nonstate\_MassViolence=Nonstate\_Nonstate\_MassViolence\_sum,

Nonstate\_state\_Threats=Nonstate\_state\_Threats\_sum,Nonstate\_state\_AttacksAssaults=Nonstate\_state\_AttacksAssaults\_sum,Nonstate\_state\_MassViolence=Nonstate\_state\_MassViolence\_sum,

state\_Nonstate\_Threats=state\_Nonstate\_Threats\_sum,state\_Nonstate\_AttacksAssaults=state\_Nonstate\_AttacksAssaults\_sum,state\_Nonstate\_MassViolence=state\_Nonstate\_MassViolence\_sum,

state\_state\_Threats=state\_state\_Threats\_sum,state\_state\_AttacksAssaults=state\_state\_AttacksAssaults\_sum,state\_state\_MassViolence=state\_state\_MassViolence\_sum

)

return(aggregated\_dataSet)

}

##########################################################################################################

######Adding variables################################

combined\_data\_t1=read.csv("combined\_data\_task1.csv",stringsAsFactors = FALSE)

Typology\_Any\_Intl<- read.csv("Typology\_Any\_Intl.csv",stringsAsFactors = FALSE)

Typology\_Intl\_Any<- read.csv("Typology\_Intl\_Any.csv",stringsAsFactors = FALSE)

Typology\_Nonstate\_Nonstate<- read.csv("Typology\_Nonstate\_nonstate.csv",stringsAsFactors = FALSE)

Typology\_Nonstate\_State<- read.csv("Typology\_Nonstate\_State.csv",stringsAsFactors = FALSE)

Typology\_State\_Nonstate<- read.csv("Typology\_State\_Nonstate.csv",stringsAsFactors = FALSE)

Typology\_State\_State<- read.csv("Typology\_State\_State.csv",stringsAsFactors = FALSE)

################################################################################################################

#typology data preprocessing

Year.Month<-apply(Typology\_Any\_Intl[,c("YEAR","MONTH")],1,function(x) create\_typology\_year\_mnonth\_column(x[1],x[2]))

Typology\_Any\_Intl<-cbind(Typology\_Any\_Intl,Year.Month)

Year.Month<-apply(Typology\_Intl\_Any[,c("YEAR","MONTH")],1,function(x) create\_typology\_year\_mnonth\_column(x[1],x[2]))

Typology\_Intl\_Any<-cbind(Typology\_Intl\_Any,Year.Month)

Year.Month<-apply(Typology\_Nonstate\_Nonstate[,c("YEAR","MONTH")],1,function(x) create\_typology\_year\_mnonth\_column(x[1],x[2]))

Typology\_Nonstate\_Nonstate<-cbind(Typology\_Nonstate\_Nonstate,Year.Month)

Year.Month<-apply(Typology\_Nonstate\_State[,c("YEAR","MONTH")],1,function(x) create\_typology\_year\_mnonth\_column(x[1],x[2]))

Typology\_Nonstate\_State<-cbind(Typology\_Nonstate\_State,Year.Month)

Year.Month<-apply(Typology\_State\_Nonstate[,c("YEAR","MONTH")],1,function(x) create\_typology\_year\_mnonth\_column(x[1],x[2]))

Typology\_State\_Nonstate<-cbind(Typology\_State\_Nonstate,Year.Month)

Year.Month<-apply(Typology\_State\_State[,c("YEAR","MONTH")],1,function(x) create\_typology\_year\_mnonth\_column(x[1],x[2]))

Typology\_State\_State<-cbind(Typology\_State\_State,Year.Month)

###########copying variables

Any\_Intl\_data<-apply(combined\_data\_t1,1,function(x) get\_Any\_Intel\_Data(x))

Any\_Intl\_data\_c<-t(Any\_Intl\_data)

Any\_Intl\_df <- as.data.frame(Any\_Intl\_data\_c,stringsAsFactors=FALSE)

combined\_data\_t2<-cbind(combined\_data\_t1,Any\_Intl\_df)

Intl\_Any\_data<-apply(combined\_data\_t1,1,function(x) get\_Intel\_Any\_Data(x))

Intl\_Any\_data\_c<-t(Intl\_Any\_data)

Intl\_Any\_df <- as.data.frame(Intl\_Any\_data\_c,stringsAsFactors=FALSE)

combined\_data\_t3<-cbind(combined\_data\_t2,Intl\_Any\_df)

Nonstate\_Nonstate\_data<-apply(combined\_data\_t1,1,function(x) get\_Nonstate\_Nonstate\_Data(x))

Nonstate\_Nonstate\_data\_c<-t(Nonstate\_Nonstate\_data)

Nonstate\_Nonstate\_df <- as.data.frame(Nonstate\_Nonstate\_data\_c,stringsAsFactors=FALSE)

combined\_data\_t4<-cbind(combined\_data\_t3,Nonstate\_Nonstate\_df)

Nonstate\_State\_data<-apply(combined\_data\_t1,1,function(x) get\_Nonstate\_state\_Data(x))

Nonstate\_State\_data\_c<-t(Nonstate\_State\_data)

Nonstate\_State\_df <- as.data.frame(Nonstate\_State\_data\_c,stringsAsFactors=FALSE)

combined\_data\_t5<-cbind(combined\_data\_t4,Nonstate\_State\_df)

State\_Nonstate\_data<-apply(combined\_data\_t1,1,function(x) get\_State\_Nonstate\_Data(x))

State\_Nonstate\_data\_c<-t(State\_Nonstate\_data)

State\_Nonstate\_df <- as.data.frame(State\_Nonstate\_data\_c,stringsAsFactors=FALSE)

combined\_data\_t6<-cbind(combined\_data\_t5,State\_Nonstate\_df)

State\_State\_data<-apply(combined\_data\_t1,1,function(x) get\_State\_State\_Data(x))

State\_State\_data\_c<-t(State\_State\_data)

State\_State\_df <- as.data.frame(State\_State\_data\_c,stringsAsFactors=FALSE)

combined\_data\_t7<-cbind(combined\_data\_t6,State\_State\_df)

combined\_dataSet\_final=combined\_data\_t7

write.csv(combined\_dataSet\_final, file ="combined\_data\_task2\_new\_typologies\_04\_05\_016.csv")

#########################################################################################

#####aggregating data by election id############################

unique\_election\_IDs<-unique(combined\_dataSet\_final$ElectionID)

aggregated\_data<-lapply(unique\_election\_IDs,function(x) Group\_Combined\_Data\_By\_ElectionID(x))

aggregated\_data\_c<-matrix(unlist(aggregated\_data),ncol = 22,byrow = T)

aggregated\_data\_df <- as.data.frame(aggregated\_data\_c,stringsAsFactors=FALSE)

aggregated\_data\_df<-rename(aggregated\_data\_df,c("V1"="Country","V2"="ISO.UN.Code","V3"=

"COW.Code","V4"="ElectionID",

"V5"="Any\_Intl\_Threats","V6"="Any\_Intl\_AttacksAssaults","V7"="Any\_Intl\_MassViolence",

"V8"="Intl\_Any\_Threats","V9"="Intl\_Any\_AttacksAssaults","V10"="Intl\_Any\_MassViolence\_MassViolence",

"V11"="Nonstate\_Nonstate\_Threats","V12"="Nonstate\_Nonstate\_AttacksAssaults","V13"="Nonstate\_Nonstate\_MassViolence",

"V14"="Nonstate\_state\_Threats","V15"="Nonstate\_state\_AttacksAssaults","V16"="Nonstate\_state\_MassViolence",

"V17"="state\_Nonstate\_Threats","V18"="state\_Nonstate\_AttacksAssaults","V19"="state\_Nonstate\_MassViolence",

"V20"="state\_state\_Threats","V21"="state\_state\_AttacksAssaults","V22"="state\_state\_MassViolence"))

write.csv(aggregated\_data\_df, file = "CREV-26-05-16.csv")