Quantile Analysis

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Load in packages.

```
library(tidyverse)
library(dplyr)
library(readr)
library(readxl)
library(naniar)
library("readr")
library("microsynth")
library("LowRankQP")
#install.packages("quantreg")
library(quantreg)

setwd('/Users/michelle/Documents/UKR-airports')
data <- read_csv("data/SCM_data.csv")
```

Log several variables.

```
data2 <- data %>%
  select(Country.Name, year, Foreign.direct.investment.net.inflows.pct.of.GDP, fatalities.y.Battles, fa

data2$ln_pass <- log1p(data2$total.passengers.in)
data2$ln_battle_fatalities <- log1p(data2$fatalities.y.Battles)
data2$ln_civilian_violence_fatalities <- log1p(data2$fatalities.y.Violence.against.civilians)
data2$ln_events <- log1p(data2$count.events.y.All.types.of.violent.conflict)

#data2$ln_pass <- replace(data2$ln_pass, is.infinite(data2$ln_pass) & data2$ln_pass < 0, 0)
#data2$ln_battle_fatalities <- replace(data2$ln_battle_fatalities, is.infinite(data2$ln_battle_fataliti
#data2$ln_civilian_violence_fatalities <- replace(data2$ln_civilian_violence_fatalities, is.infinite(da
#data2$ln_events <- replace(data2$ln_events, is.infinite(data2$ln_events) & data2$ln_events < 0, 0)
```

Basic quantile model: FDI on ln(passengers_in_total)

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data2, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1))

qr.model[["coefficients"]]
```

```
##                tau= 0.1   tau= 0.2   tau= 0.3    tau= 0.4    tau= 0.5
## (Intercept)  0.33151929 0.94025522 1.46871307 2.101721082 2.688581824
```

```
## ln_pass     -0.01314977 0.01283855 0.01519595 0.008296265 0.009710437
##               tau= 0.6    tau= 0.7  tau= 0.8  tau= 0.9  tau= 1.0
## (Intercept) 3.480699573  4.52412383  6.828451 11.995558 280.14551
## ln_pass     0.002297376 -0.01954095 -0.104196 -0.259189 -14.19781
```

(1): Running the quantile regression with ACLED numbers as a control. From the documentation: "The WEIGHT statement specifies a weight variable in the input data set. To request weighted quantile regression, place the weights in a variable. The values of the WEIGHT variable can be nonintegral and are not truncated. Observations with nonpositive or missing values for the weight variable do not contribute to the fit of the model." https://support.sas.com/documentation/onlinedoc/stat/142/qreg.pdf

Weighing by battle fatalities:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data2, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = ln_battle_fatalities)

qr.model[["coefficients"]]
```

```
##              tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.14440106 0.48737247 1.00393639 1.34333861 1.68919943 2.14019963
## ln_pass     0.03965494 0.05024135 0.03805129 0.05386086 0.05606217 0.05178861
##              tau= 0.7  tau= 0.8     tau= 0.9  tau= 1.0
## (Intercept) 2.59030845 3.1975675  4.971522454 38.942865
## ln_pass     0.05473321 0.0597402 -0.004906635  8.613608
```

```
#By using battle fatalities as weights, this shows the effects of passengers on
#FDI where battle numbers are higher
```

Weighing by civilian violence fatalities:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data2, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = ln_civilian_violence_fatalities)

qr.model[["coefficients"]]
```

```
##              tau= 0.1   tau= 0.2   tau= 0.3  tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.12449599 0.39759005 0.98316619 1.3359173 1.66129507 2.11999261
## ln_pass     0.04550236 0.06398363 0.04377282 0.0580259 0.06441087 0.05397141
##              tau= 0.7   tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.60581166 3.41047904  5.41557013 237.35551
## ln_pass     0.05790719 0.04738953 -0.03453349 -14.06653
```

```
#By using civilian violence fatalities as weights, this shows the effects of
#passengers on FDI where civilian violence numbers are higher
```

Weighing by number of violent events, all types of violent conflict:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data2, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = ln_events)

qr.model[["coefficients"]]
```

```
##                tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.14440106 0.55978363 1.06894190 1.46272973 1.98912793 2.53049662
## ln_pass     0.02391971 0.03938693 0.03323556 0.04577842 0.04323158 0.04320444
##                tau= 0.7     tau= 0.8   tau= 0.9  tau= 1.0
## (Intercept) 3.28518934  4.471176846  7.9132347 237.35551
## ln_pass     0.02782911 -0.002677161 -0.1870566 -14.06653
```

```
#By using number of violent events as weights, this shows the effects of the
#number of violent events (theoretically those picked up by news outlets in
#order to be included in ACLED data) on FDI where civilian violence numbers are
#higher. Maybe this shows the impact of total perceived/reported amount of violence.
```

(2) Incorporating lags/leads on FDI We should be regressing THIS year's passenger and conflict numbers on NEXT year's FDI numbers. Therefore we should put a lead() on FDI so that each observation captures passenger and conflict numbers from this year and FDI numbers from NEXT year.

```
data3 <- data2 %>%
  group_by(Country.Name) %>%
  arrange(year) %>%
  mutate(lead_FDI = lead(Foreign.direct.investment.net.inflows.pct.of.GDP)) %>%
  filter(year < 2023)
```

No weights:

```
qr.model <- rq(lead_FDI ~ ln_pass,
               data = data3, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1))

qr.model[["coefficients"]]
```

```
##                  tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4  tau= 0.5
## (Intercept)  0.274796791 0.84495047 1.45343421 2.03374734 2.6194397
## ln_pass     -0.007075528 0.02274866 0.01716171 0.01128004 0.0149581
##                  tau= 0.6    tau= 0.7  tau= 0.8   tau= 0.9  tau= 1.0
## (Intercept) 3.4757102400   4.50950043  6.795414 11.9955584 280.14551
## ln_pass     0.0008870602 -0.02108548 -0.111292 -0.2687082 -14.31024
```

Weighing by battle fatalities:

```
qr.model <- rq(lead_FDI ~ ln_pass,
               data = data3, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = ln_battle_fatalities)

qr.model[["coefficients"]]
```

```
##                tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.14440106 0.43581493 0.98316619 1.30269498 1.59825986 2.05805641
## ln_pass     0.03299816 0.03878919 0.03546371 0.04398073 0.05994012 0.04843401
##                tau= 0.7   tau= 0.8     tau= 0.9  tau= 1.0
## (Intercept) 2.55226969 3.10040078 4.7567791402 38.942865
## ln_pass     0.03948651 0.06287562 0.0006689216  6.426857
```

```r
#By using battle fatalities as weights, this shows the effects of passengers on
#next year's FDI, where battle numbers are higher.
```

Weighing by civilian violence fatalities:

```r
qr.model <- rq(lead_FDI ~ ln_pass,
              data = data3, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
              weight = ln_civilian_violence_fatalities)

qr.model[["coefficients"]]
```

```
##                tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4  tau= 0.5   tau= 0.6
## (Intercept) 0.13374624 0.36276291 0.82123815 1.20275464 1.5138933 2.03374734
## ln_pass     0.04252409 0.06211623 0.05244532 0.06973376 0.0684468 0.05825813
##                tau= 0.7  tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.55226969 3.2851893  5.18553684 38.942865
## ln_pass     0.05073138 0.0549127 -0.01921237  6.426857
```

```r
#By using civilian violence fatalities as weights, this shows the effects of
#passengers on next year's FDI where civilian violence numbers are higher.
```

Weighing by number of violent events, all types of violent conflict:

```r
qr.model <- rq(lead_FDI ~ ln_pass,
              data = data3, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
              weight = ln_events)

qr.model[["coefficients"]]
```

```
##              tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4  tau= 0.5   tau= 0.6
## (Intercept) 0.160320 0.53169091 1.03378939 1.44347193 1.9006674 2.35091904
## ln_pass     0.033735 0.04875219 0.03715887 0.04936572 0.0450196 0.05508985
##                tau= 0.7     tau= 0.8    tau= 0.9   tau= 1.0
## (Intercept) 3.10040078 4.396540773  7.9132347 237.35551
## ln_pass     0.04021105 0.005515503 -0.1896097 -14.06653
```

```r
#By using number of violent events as weights, this shows the effects of the
#number of violent events (theoretically those picked up by news outlets in
#order to be included in ACLED data) on next year's FDI where civilian violence
#numbers are higher. Maybe this reflects the impact of total perceived/reported
#amount of violence.
```

(3) Lagging violence variables

Add a lag(violence) variable, so that we can test the effect of this year's passengers on this year's FDI, where last year's violent conflict numbers are higher.

```r
data4 <- data2 %>%
  group_by(Country.Name) %>%
  arrange(year) %>%
```

```r
  mutate(lag_ln_battle_fatalities = lag(ln_battle_fatalities),
         lag_ln_civilian_violence_fatalities = lag(ln_civilian_violence_fatalities),
         lag_ln_events = lag(ln_events)) %>%
  filter(year > 2010)
```

Weighing by battle fatalities:

```r
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data4, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = lag_ln_battle_fatalities)

qr.model[["coefficients"]]
```

```
##               tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.14440106 0.48737247 1.00393639 1.34333861 1.62887391 2.10248371
## ln_pass     0.03575474 0.03359426 0.03392437 0.04385178 0.05592563 0.04553819
##               tau= 0.7   tau= 0.8     tau= 0.9  tau= 1.0
## (Intercept) 2.58149705 3.17633493 4.765497e+00 38.942865
## ln_pass     0.03908585 0.05174768 5.948712e-17  5.317809
```

```r
#By using battle fatalities as weights, this shows the effects of passengers on
#FDI, where last year's battle numbers are higher.
```

Weighing by civilian violence fatalities:

```r
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data4, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = lag_ln_civilian_violence_fatalities)

qr.model[["coefficients"]]
```

```
##               tau= 0.1   tau= 0.2  tau= 0.3   tau= 0.4 tau= 0.5   tau= 0.6
## (Intercept) 0.12449599 0.39759005 1.0023407 1.30975248 1.624466 2.10248371
## ln_pass     0.04358868 0.05983407 0.0417771 0.05929936 0.061103 0.05371692
##               tau= 0.7   tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.59030845 3.36279831  5.17508493 38.942865
## ln_pass     0.04031182 0.04462408 -0.02188709  5.317809
```

```r
#By using civilian violence fatalities as weights, this shows the effects of
#passengers on next year's FDI where civilian violence numbers are higher.
```

Weighing by number of violent events, all types of violent conflict:

```r
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data4, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = lag_ln_events)

qr.model[["coefficients"]]
```

```
##               tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.14440106 0.55978363 1.07508351 1.46272269 1.98912793 2.45649403
## ln_pass     0.03575474 0.04337805 0.03277541 0.04777319 0.04113391 0.04636196
##               tau= 0.7      tau= 0.8   tau= 0.9  tau= 1.0
## (Intercept) 3.22476397  4.4479279873  7.6197559 237.35551
## ln_pass     0.03195586 -0.0003013826 -0.1634084 -14.06653
```

```
#By using number of violent events as weights, this shows the effects of the
#number of violent events the previous year (theoretically those picked up by
#news outlets in order to be included in ACLED data) on FDI where civilian
#violence numbers are higher. Maybe this reflects the impact of total
#perceived/reported amount of violence.
```

(4) Running the original regression with no weights, but removing countries with less than >100 battle deaths

Let's adjust data to remove COUNTRY+YEAR OBSERVATIONS without enough violence. (>100 battle deaths). We can't just remove all countries with a year or two of insuffiecent violence, since we would then have practically no observations left (just Pakistan and a handful of other countries). It is enough to see what is the within-country and within-year effect of passenger_total on FDI, given that significant battle violence occurred that year.

```
data5 <- data4 %>%
  filter(fatalities.y.Battles > 100)
```

No weights:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data5, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1))

qr.model[["coefficients"]]
```

```
##               tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.18339579 0.64450097 1.03137876 1.40873498 1.62526707 2.39118081
## ln_pass     0.04123577 0.04744107 0.03601632 0.04030899 0.06104065 0.02757168
##               tau= 0.7   tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.74657132 3.36279831  4.97152245 38.942865
## ln_pass     0.01774368 0.02252881 -0.06069861 -2.170665
```

```
#Effects of passengers on FDI within a year/country, given that battle
#fatalities in that country were higher than 100 in that year.
```

Weighing by battle fatalities:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
               data = data5, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
               weight = ln_battle_fatalities)

qr.model[["coefficients"]]
```

```
##              tau= 0.1  tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.1444011 0.5300608 1.00393639 1.34333861 1.59825986 2.27561207
## ln_pass     0.0415860 0.0569407 0.03816398 0.05519852 0.06339035 0.03618994
##               tau= 0.7   tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.65592559 3.31414783  4.90909802 38.942865
## ln_pass     0.02404352 0.02585139 -0.05646044 -2.170665
```

```
#Effects of passengers on FDI within a year/country, given that battle
#fatalities in that country were higher than 100 in that year.
#By using battle fatalities as weights, this shows the effects of passengers on
#FDI, where battle numbers are higher.
```

Weighing by civilian violence fatalities:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
              data = data5, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
              weight = ln_civilian_violence_fatalities)

qr.model[["coefficients"]]
```

```
##               tau= 0.1   tau= 0.2   tau= 0.3  tau= 0.4   tau= 0.5  tau= 0.6
## (Intercept) 0.14440106 0.49070394 1.00393639 1.3433386 1.59825986 2.3118986
## ln_pass     0.06244494 0.07196155 0.05894852 0.0732513 0.07169453 0.0386139
##               tau= 0.7   tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.65592559 3.32336390  4.97152245 38.942865
## ln_pass     0.02404352 0.02522198 -0.06069861 -2.170665
```

```
#Effects of passengers on FDI within a year/country, given that battle
#fatalities in that country were higher than 100 in that year.
#By using civilian violence fatalities as weights, this shows the effects of
#passengers on FDI where civilian violence numbers are higher.
```

Weighing by number of violent events, all types of violent conflict:

```
qr.model <- rq(Foreign.direct.investment.net.inflows.pct.of.GDP ~ ln_pass,
              data = data5, tau = c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1),
              weight = ln_events)

qr.model[["coefficients"]]
```

```
##               tau= 0.1   tau= 0.2   tau= 0.3   tau= 0.4   tau= 0.5   tau= 0.6
## (Intercept) 0.14440106 0.53006079 1.00393639 1.30269498 1.52754030 2.21213569
## ln_pass     0.04473306 0.06464509 0.03816398 0.05879371 0.06762888 0.04092354
##              tau= 0.7   tau= 0.8    tau= 0.9  tau= 1.0
## (Intercept) 2.6519345 3.31414783  4.90909802 38.942865
## ln_pass     0.0243209 0.02585139 -0.05646044 -2.170665
```

```
#Effects of passengers on FDI within a year/country, given that battle
#fatalities in that country were higher than 100 in that year.
#By using number of violent events as weights, this shows the effects of the
#number of violent events (theoretically those picked up by news outlets in
```

```
#order to be included in ACLED data) on FDI where civilian violence
#numbers are higher. Maybe this reflects the impact of total perceived/reported
#amount of violence.
```

(4) Get GDP numbers from Ukraine IMF report Convert using exchange rates Put into dataset in SCM.Rmd Multiply with FDI % to get total FDI column Export new dataset Rerun 1,2,3 with total FDI

(5) Regressing on log(passenger_pct)

(6) Regressing on passenger_spike