Week 7 Methods: Migration

ECON 125: The Science of Population

Setup

Today, we analyze Mexican migration

We use a 10% sample drawn from the 2020 Mexican census

The main dataset includes:

- Household-level and individual-level variables
- One observation per adult aged 20-64

Later, we will merge this dataset with municipality-level data on area poverty

Start by setting up R and loading the first dataset

```
# Load tidyverse and clear the R environment
library(tidyverse)
rm(list=ls())

# Load dataset
load(url("https://github.com/tomvogl/econ125/raw/main/data/mex2020.rds"

# Ask R to not use scientific notation
options(scipen = 999)
```

Glimpse

```r
glimpse(mex2020)
```

```
## Rows: 8,001,516
## Columns: 15
## $ hhid      <dbl> 1000, 1000, 2000, 2000, 2000, 3000, 4000, 4000, 40
## $ hhwt      <dbl> 59, 59, 59, 59, 59, 59, 59, 59, 59, 59, 59, 59, 59
## $ perwt     <dbl> 59, 59, 59, 59, 59, 59, 59, 59, 59, 59, 59, 59, 59
## $ mun       <int> 1001, 1001, 1001, 1001, 1001, 1001, 1001, 1001, 10
## $ locsize   <fct> "100,000 or more inhabitants", "100,000 or more in
## $ hhsize    <dbl> 3, 3, 4, 4, 4, 1, 3, 3, 3, 4, 4, 4, 4, 4, 4, 1, 4,
## $ migrants  <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
## $ remitt    <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
## $ head      <dbl> 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1,
## $ male      <dbl> 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1,
## $ age       <dbl> 55, 21, 45, 42, 20, 60, 62, 54, 32, 52, 53, 21, 20
## $ educ      <dbl> 16, 14, 17, 17, 13, 17, 18, 18, 16, 16, 12, 14, 13
## $ country5  <fct> "Mexico", "Mexico", "Mexico", "Mexico", "Mexico",
## $ mun5      <dbl> 1001, 1001, 1001, 1001, 1001, 1001, 1001, 1001, 10
## $ migcause5 <fct> "NIU (not in universe)", "NIU (not in universe)",
```

Understanding Emigration

Key variables for studying emigration:

- `migrants` = number of HH members who left Mexico in last 5 years
- `hhsize` = number of HH members currently
- `remitt` = 1 if HH received remittances in last 5 years, 0 otherwise

```
mex2020 |> summarise(avg_migrants = mean(migrants),
                     avg_hhsize = mean(hhsize),
                     share_remitt = mean(remitt))
```

```
## # A tibble: 1 x 3
##   avg_migrants avg_hhsize share_remitt
##          <dbl>      <dbl>        <dbl>
## 1       0.0311       4.60        0.102
```

Could note some interesting facts, but the unit of observation is wrong

Individual vs. Household Level

The variables on the previous slide are HH-level

Confusing to analyze them in individual-level data

Let's create a HH-level data frame by keeping only HH heads

```
mex2020_hh <- mex2020 |> filter(head==1)

mex2020_hh |> summarise(avg_migrants = mean(migrants),
                        avg_hhsize = mean(hhsize),
                        share_remitt = mean(remitt))
```

```
## # A tibble: 1 x 3
##   avg_migrants avg_hhsize share_remitt
##          <dbl>      <dbl>        <dbl>
## 1       0.0322       3.95       0.0996
```

Key findings

- Less than 1% of HH members emigrated in last 5 years
- 10% of HHs received remittances in last 5 years $\rightarrow$ many long-ago emigrants

Distribution of Number of Migrants

What is the distribution of migrants per household?

Instead of `group_by()`, convenient to use `count()`

```
mex2020_hh |> count(migrants) |> mutate(pct = 100*n/sum(n))
```

```
## # A tibble: 13 x 3
##    migrants       n        pct
##       <dbl>   <int>      <dbl>
##  1        0 3035173 97.3
##  2        1   72336  2.32
##  3        2    8525  0.273
##  4        3    1955  0.0627
##  5        4     732  0.0235
##  6        5     257  0.00824
##  7        6      63  0.00202
##  8        7      35  0.00112
##  9        8      16  0.000513
## 10        9       5  0.000160
## 11       10       1  0.0000321
## 12       13       2  0.0000641
## 13       14       1  0.0000321
```

Characteristics of Migrant-Sending vs. Non-Migrant-Sending HHs

Can we learn about determinants of emigration by looking at HH characteristics?

Let's compute average characteristics for HH with and without recent emigrants

```
mex2020_hh <- mex2020_hh |> mutate(anymigrants = if_else(migrants>0, 1,

mex2020_hh |>
  group_by(anymigrants) |>
  summarise(avg_size = mean(hhsize),
            avg_age = mean(age),
            avg_educ = mean(educ),
            share_male = mean(male),
            n = n())
```

```
## # A tibble: 2 x 6
##   anymigrants avg_size avg_age avg_educ share_male       n
##         <dbl>    <dbl>   <dbl>    <dbl>      <dbl>   <int>
## 1           0     3.95    43.7     8.24      0.737 3035173
## 2           1     4.02    44.3     7.73      0.584   83928
```

HHs with recent emigrants have less educated heads → negative selection?

Not so fast → more female heads, likely due to endogenous HH structure

Area-Level Predictors of Emigration

To avoid bias from endogenous HHs, better to look at area predictors

Dataset already has locality size → less than 2500 considered rural

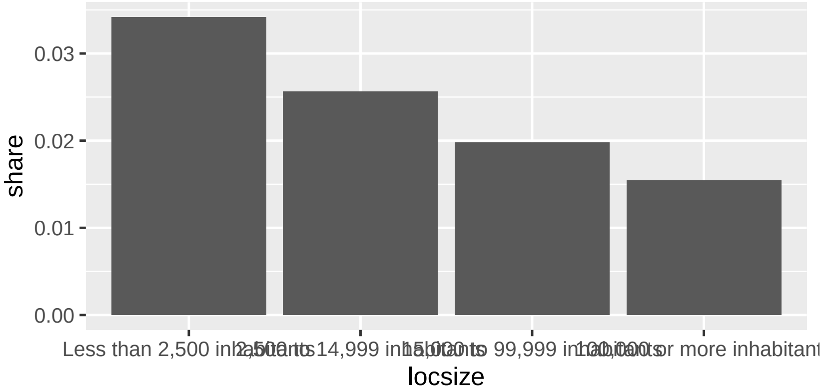
```
mex2020_hh |> count(locsize) |> mutate(pct = 100*n/sum(n))
```

```
## # A tibble: 4 x 3
##   locsize                              n   pct
##   <fct>                            <int> <dbl>
## 1 Less than 2,500 inhabitants    1326019  42.5
## 2 2,500 to 14,999 inhabitants     824989  26.4
## 3 15,000 to 99,999 inhabitants    581253  18.6
## 4 100,000 or more inhabitants     386840  12.4
```

Emigration Shares by Locality Size

HHs in smaller (generally more rural) localities more likely to send migrants

```
table <-
  mex2020_hh |>
  group_by(locsize) |>
  summarise(share = mean(anymigrants))

ggplot(table, aes(x=locsize,y=share)) +
  geom_col()
```



Introducing Outside Data on Area Poverty

Locality size a bit hard to interpret

We'll use the Mexican government's measures of municipality "marginalization"

```
marg2020 <- read_csv(url("https://github.com/tomvogl/econ125/raw/main/d
glimpse(marg2020)
```

```
## Rows: 2,469
## Columns: 9
## $ state      <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2
## $ name_state <chr> "Aguascalientes", "Aguascalientes", "Aguascalient
## $ mun        <dbl> 1001, 1002, 1003, 1004, 1005, 1006, 1007, 1008, 1
## $ name_mun   <chr> "Aguascalientes", "Asientos", "Calvillo", "Cosío"
## $ population <dbl> 948990, 51536, 58250, 17000, 129929, 47646, 57369
## $ index_raw  <dbl> 60.31880, 56.54607, 57.05825, 57.11403, 59.01176,
## $ grade      <chr> "1 Very low", "1 Very low", "1 Very low", "1 Very
## $ index_norm <dbl> 0.9445084, 0.8854328, 0.8934528, 0.8943262, 0.924
## $ index_rank <dbl> 2435, 1816, 1932, 1948, 2323, 2265, 2076, 2048, 1
```

Introducing Outside Data on Area Poverty

The data include a coarse “grade” and a continuous “index” of marginalization

For simplicity, we’ll use the 5-category “grade”

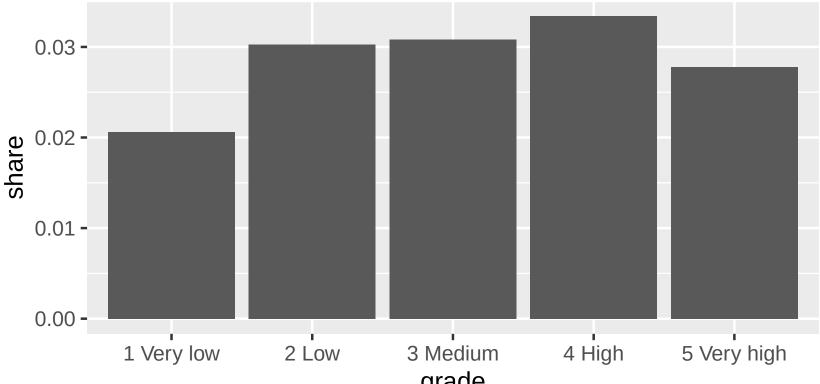
```
marg2020 |> count(grade) |> mutate(pct = n/sum(n))
```

```
## # A tibble: 5 x 3
##   grade             n    pct
##   <chr>         <int>  <dbl>
## 1 1 Very low      655 0.265
## 2 2 Low           530 0.215
## 3 3 Medium        494 0.200
## 4 4 High          586 0.237
## 5 5 Very high     204 0.0826
```

Emigration Shares by Municipality Marginalization

HHs in poorer (but not poorest) areas more likely to send migrants

```
mex2020_hh <- mex2020_hh |> left_join(marg2020, by = "mun")

table <- mex2020_hh |> group_by(grade) |>
  summarise(share = mean(anymigrants))

ggplot(table, aes(x = grade, y = share)) +
  geom_col()
```



Interpretation

Mexican migrants less likely to come from poorest/richest parts of the country

Highest share of migrant-sending households is in “high” marginalization munis

Consistent with the results Abramitzky and Boustan report in their article

Mexican migrants come from the middle of the distribution

No strong pattern of positive or negative selection

Immigration

The results so far have been about **em**migration: leaving Mexico

The data also tell us about **im**migration: coming to Mexico

`country5` = **individual's** residence in 2015 → switch back to individual-level

```
mex2020 |> count(country5) |> mutate(pct = 100*n/sum(n)) |> arrange(-n)
```

```
## # A tibble: 40 x 3
##    country5             n      pct
##    <fct>            <int>    <dbl>
##  1 Mexico         7953641 99.4
##  2 United States    41206  0.515
##  3 Venezuela          844  0.0105
##  4 Guatemala          809  0.0101
##  5 Honduras           667  0.00834
##  6 Colombia           481  0.00601
##  7 Canada             461  0.00576
##  8 Cuba               371  0.00464
##  9 El Salvador        351  0.00439
## 10 Spain              272  0.00340
## # i 30 more rows
```

Immigration Shares by Municipality Marginalization: Table

Basically all immigrants to Mexico in 2015-2020 came from the US

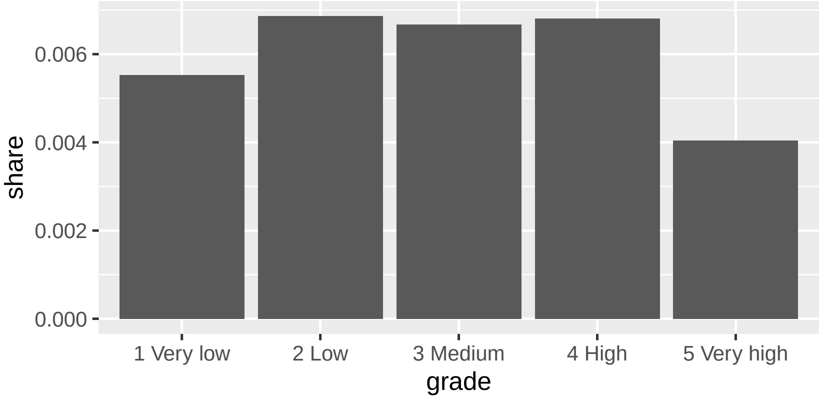
Unsurprisingly, mostly went to medium marginalization municipalities

```
mex2020 <- mex2020 |>
  mutate(immigrant = if_else(country5!="Mexico", 1, 0)) |>
  left_join(marg2020, by = "mun")

table <- mex2020 |>
  group_by(grade) |>
  summarise(share = mean(immigrant))

table
```

```
## # A tibble: 5 x 2
##   grade         share
##   <chr>         <dbl>
## 1 1 Very low  0.00553
## 2 2 Low       0.00686
## 3 3 Medium    0.00667
## 4 4 High      0.00680
## 5 5 Very high 0.00404
```

Immigration Shares by Municipality Marginalization: Graph

```r
ggplot(table, aes(x = grade, y = share)) +
  geom_col()
```



Similar to the emigration graph, but some differences

- More immigrants settling in "very low" than in "very high"
- Incentive to relocate to higher opportunity areas, even if returning to Mexico

Internal Migration

Mexico also has a lot of internal migration

Here we will define internal migration as movement across municipalities

How common was internal migration in 2015-20? Check whether `mun` == `mun5`

Some individuals have `NA` for `mun5`, mostly because they lived outside Mexico

```
summary(mex2020$mun5)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    1001   12078   18017   18209   24012   32058   78990
```

Drop `NA`s and generate internal migration dummy variable

```
mex2020 <-
  mex2020 |>
  drop_na(mun5) |>
  mutate(migrant = if_else(mun!=mun5, 1, 0))
```

Internal Migrants: Population Share and Characteristics

5% of the Mexican adult population moved municipalities during 2015-2020

```
mex2020 |> summarise(share = mean(migrant))
```

```
## # A tibble: 1 x 1
##    share
##    <dbl>
## 1 0.0507
```

How were migrants different from non-migrants?

```
mex2020 |>
  group_by(migrant) |>
  summarise(avg_age = mean(age),
            avg_educ = mean(educ),
            share_male = mean(male))
```

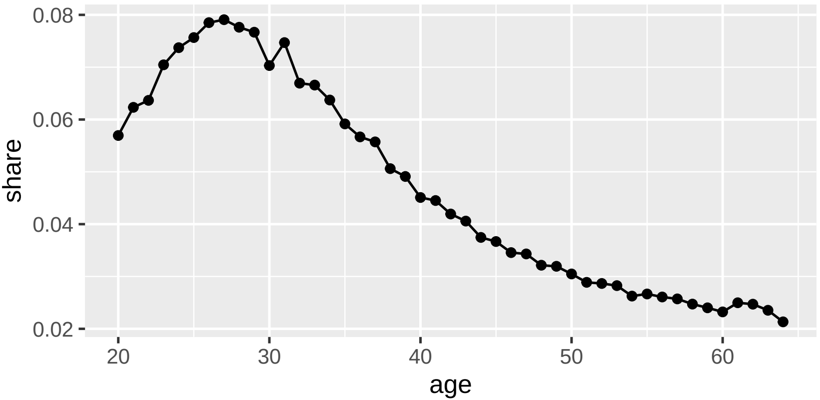
```
## # A tibble: 2 x 4
##   migrant avg_age avg_educ share_male
##     <dbl>   <dbl>    <dbl>      <dbl>
## 1       0    39.2     8.64      0.474
## 2       1    34.6    10.7       0.476
```

Selection! Migrants are younger and more educated than non-migrants

Age and Internal Migration

Let's dig into the age-migration relationship a bit more

```
table <- mex2020 |> group_by(age) |> summarise(share = mean(migrant))

ggplot(table, aes(x = age, y = share)) +
  geom_point() +
  geom_line()
```



Interpreting the Age Patterns

People in their 20s were most likely to move

- Common for young people to be more mobile
- Could reflect cohort effects $\rightarrow$ not possible to check in cross-section

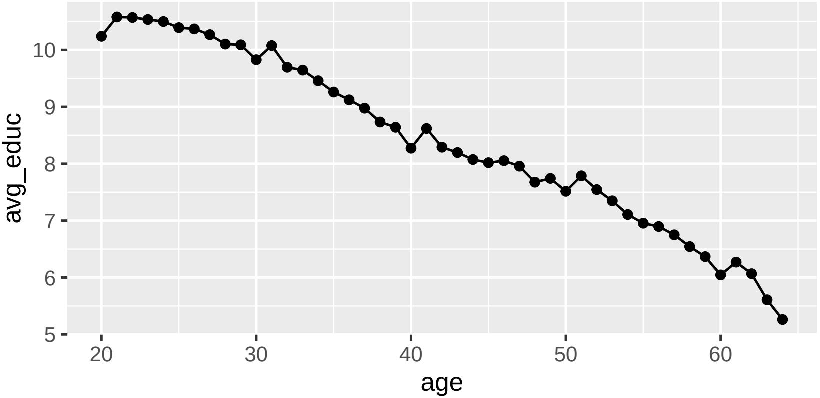
Cohort effects are likely to be important for confounding role of education

- Recent cohorts more educated, more likely to move

Age and Education

Age is related to education, but this is really a cohort phenomenon

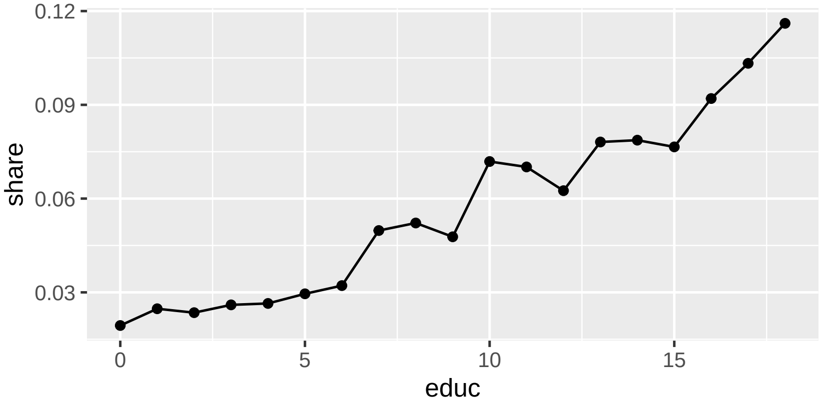
```
table <- mex2020 |> group_by(age) |> summarise(avg_educ = mean(educ))

ggplot(table, aes(x = age, y = avg_educ)) +
  geom_point() +
  geom_line()
```



Education and Internal Migration

Let's dig into the education-migration relationship a bit more

```
table <- mex2020 |> group_by(educ) |> summarise(share = mean(migrant))

ggplot(table, aes(x = educ, y = share)) +
  geom_point() +
  geom_line()
```



Very clear positive selection

Disentangling the Roles of Age and Education

How can we disentangle these two forces?

Standard approach: regression adjustment

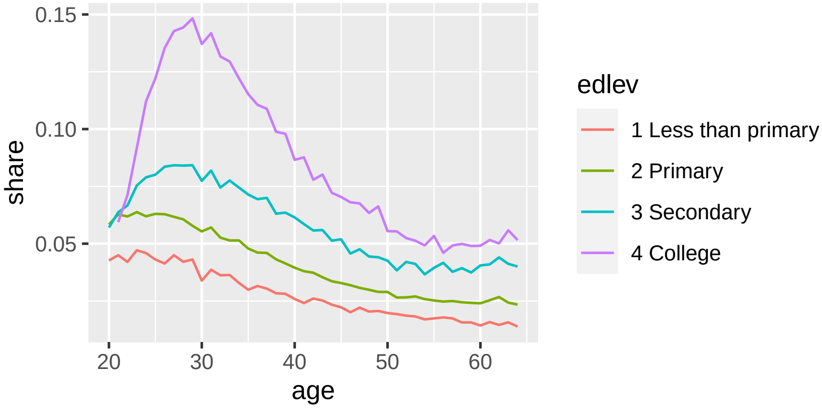
But we are not running regressions in this class!

As an alternative, we can draw separate age-migration graphs by education level

```
mex2020 <-
  mex2020 |>
  mutate(edlev = case_when(educ<6 ~ "1 Less than primary",
                           educ>=6&educ<12 ~ "2 Primary",
                           educ>=12&educ<16 ~ "3 Secondary",
                           educ>=16 ~ "4 College"))
```

Age and Internal Migration by Education Level

```r
table <- mex2020 |>
  group_by(edlev, age) |>
  summarise(share = mean(migrant))

ggplot(table, aes(x = age, y = share, color=edlev)) +
  geom_line()
```



Interpreting the Age and Education Patterns

Age and education independently predict migration

More educated migrate more at almost every age

Young migrate more than old in every education group, but peak age varies

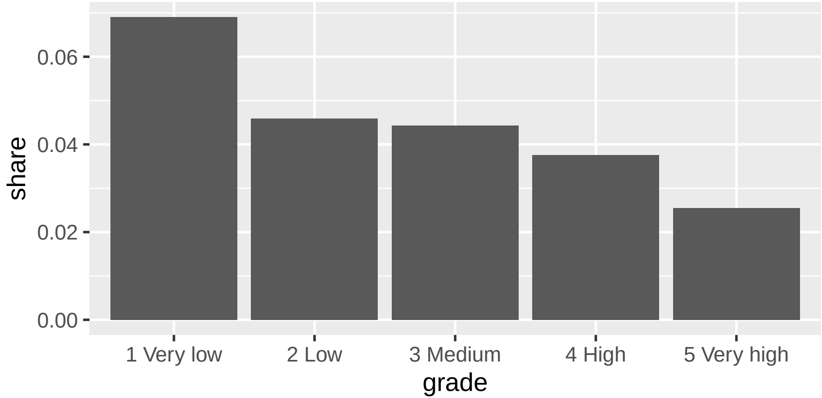
Lots of mobility for college-educated just after finishing college

But even for individuals in their 60s, migration rates highest for college, then secondary, then primary, then less

Migrant Status by Destination Municipality Marginalization

Do high opportunity areas tend to receive more internal migrants? **Yes**

```r
table <- mex2020 |> group_by(grade) |> summarise(share = mean(migrant))

ggplot(table, aes(x = grade, y = share)) +
  geom_col()
```



Origin Municipality Marginalization

Also interesting to study the marginalization level of **origin** municipalities

We need to merge in marginalization data again, this time by lagged municipality

First rename variables in the `marg2020` data frame to avoid duplicate names

```
marg2020 <- marg2020 |>
  select(mun, grade, index_rank) |>
  rename(mun5 = mun, grade5 = grade, index_rank5 = index_rank)
```

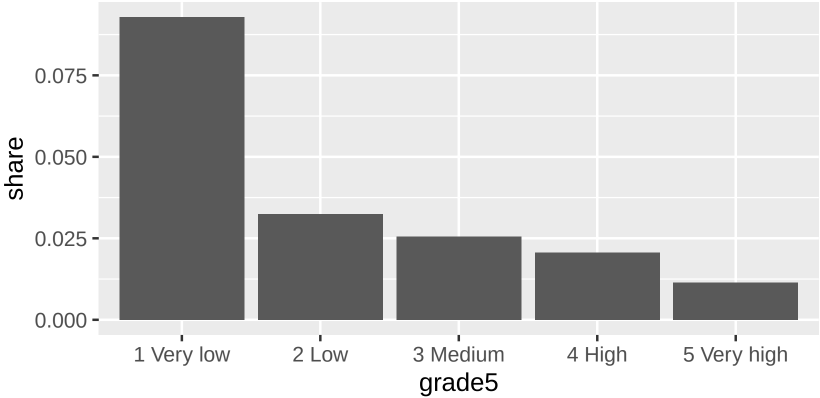
Now merge into census dataset by `mun5`

```
mex2020 <- mex2020 |>
  left_join(marg2020, by = "mun5")
```

Migrant Status by Origin Municipality Marginalization

Do low opportunity areas tend to send more internal migrants? **No**

```
table <- mex2020 |> group_by(grade5) |> summarise(share = mean(migrant)

ggplot(table, aes(x = grade5, y = share)) +
  geom_col()
```



Origin-Destination Matrix

Preceding results suggest many migrants move from *very low* to *very low*

We can check by tabulating `grade5` with `grade`

We'll deviate from `tidyverse` syntax because it's is much easier in base `R`

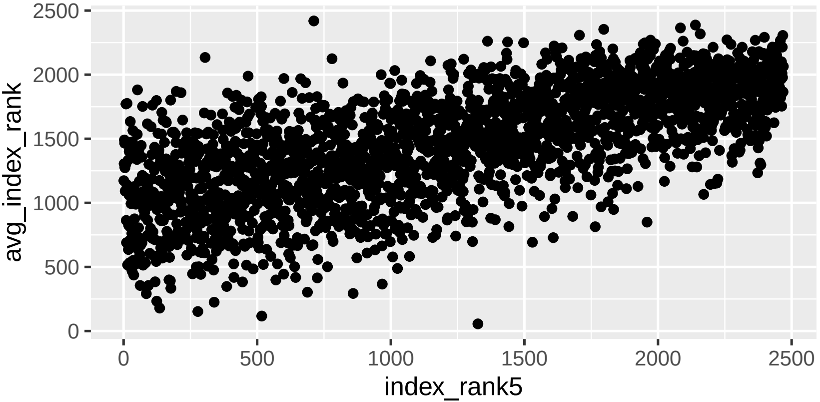
```
migrants <- mex2020 |> filter(migrant==1)

table(migrants$grade5, migrants$grade)
```

```
##
##                  1 Very low  2 Low 3 Medium 4 High 5 Very high
##    1 Very low        169135  45640    30862  28540       13435
##    2 Low              19221  10182     7805   6561        3394
##    3 Medium            9440   5678     6355   6088        1720
##    4 High              7544   4433     5386   6452        3024
##    5 Very high         3006   1728     1507   2041        2207
```

Continuous representation

Compare marginalization index ranks of origin and destination municipalities

```
table <- migrants |>
  group_by(index_rank5) |>
  summarise(avg_index_rank = mean(index_rank))

ggplot(table, aes(x=index_rank5, y=avg_index_rank)) +
  geom_point()
```



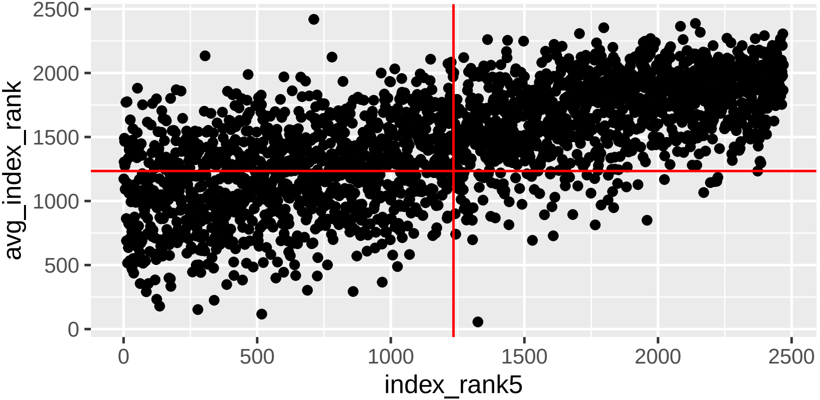
Interpreting origin-destination patterns

Lots of migration between municipalities with similar marginalization ranks

We haven't used GIS data, but some of these munis are geographically close

Most internal migration is not "moving to opportunity," but you can find it

Substantial migration from the bottom half of municipalities to the top half

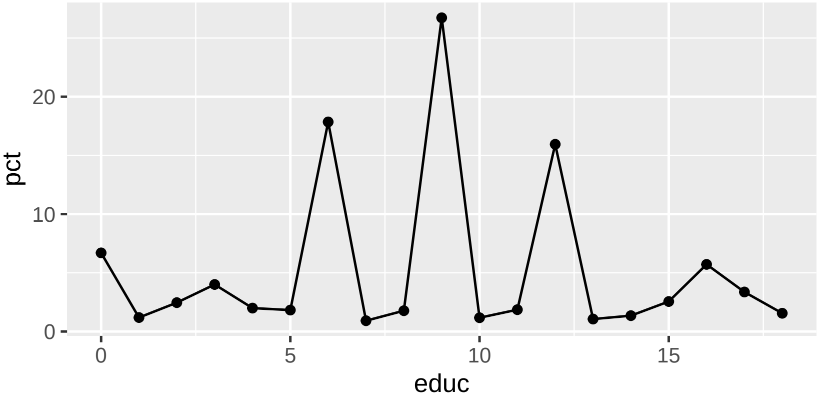


Distribution of Years of Education among Mexican Adults

PS 4 asks you to compare the education distributions of Mexican immigrants to the US and Mexicans in Mexico

One way to represent the distribution is with a histogram of years of education

```
table <- mex2020 |> count(educ) |> mutate(pct = 100*n/sum(n))
ggplot(table, aes(x=educ, y=pct)) +
  geom_point() +
  geom_line()
```



Distribution of Education Levels among Mexican Adults

Another nice way to represent it is with a tabulation of highest level completed

```
mex2020 |> count(edlev) |> mutate(pct = 100*n/sum(n))
```

```
## # A tibble: 4 x 3
##   edlev                    n   pct
##   <chr>                <int> <dbl>
## 1 1 Less than primary 1439020  18.2
## 2 2 Primary           3984566  50.3
## 3 3 Secondary         1656520  20.9
## 4 4 College            842420  10.6
```

Sampling Weights

Mexican statistical agency intentionally oversampled sparsely populated areas

- Common practice in survey sampling
- Results in raw sample not being fully representative of the Mexican population

Agency provides **sampling weights** to restore representativeness

- `hhwt` for households and `perwt` for people
- Our analysis was unweighted for simplicity, but easy to incorporate weights
- Instead of `mean(educ)`, use `weighted.mean(educ, perwt)`
- Instead of `count(educ)`, use `count(educ, wt = perwt)`
- I reran the analysis with weights - most results didn't change qualitatively
- In the final two slides, I report two results that did change somewhat

Weighted Distribution of Education Levels among Mexican Adults

The unweighted distribution of education levels was for the sample, not the pop

If we want to represent the population, we can apply sampling weights as follows

```
mex2020 |> count(edlev, wt=perwt) |> mutate(pct = 100*n/sum(n))
```

```
## # A tibble: 4 x 3
##   edlev                       n   pct
##   <chr>                   <dbl> <dbl>
## 1 1 Less than primary   7299550  10.3
## 2 2 Primary            32420340  45.8
## 3 3 Secondary          18880664  26.6
## 4 4 College            12247462  17.3
```

Compared with the unweighted distribution, this weighted distribution has a smaller share with less than primary, and a higher share with secondary or college

PS 4, Q 5, asks about the selectivity of Mexican immigrants to the US

The answer is the same using either the weighted or unweighted distribution

You will get credit for either

Revisiting the Rank Graph

Here is one other place where the results change a bit with weighting

If we estimate the origin-destination marginalization relationship using weights, the qualitative pattern is similar, but the scatterplot looks a bit different

```
table <- migrants |>
  group_by(index_rank5) |>
  summarise(avg_index_rank = weighted.mean(index_rank, perwt),
            total_weight = sum(perwt))

ggplot(table, aes(x=index_rank5, y=avg_index_rank, size = total_weight)
  geom_point()
```