### LinkedIn & IFC study of migration

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### 1 CONCEPTUAL FRAMEWORK

A city's productivity can be simply defined as the net result of contrasting forces Productivity = Agglomeration(positive) - Congestion(negative)

Where Agglomeration and Congestion are a function of various dimensions = f(Skills, Amenities, Form, Access)

- Dimensions
  - Skills, a city's aggregate stock of human capital
  - Amenities attracting skills job opportunities, housing values, cultural attractions
  - Form, the size and spatial configuration of a city (density vs. sprawl, wider metropolitan areas)
  - **Access**, a city's connectedness (or barriers) to other cities, both at home and abroad, through the transportation network
- This comparative analysis will focus on the first dimension Skills, with hints to the other ones

```
library(ggplot2) # install.packages("ggplot2")
library(dplyr)
library(knitr)
library(datasets) # initialize
library(knitr)
library(kableExtra)
library(stats)
library(stidyr)
library(stringr)
library(stats)

# getwd()
# migr <- read.csv("migration.csv",fileEncoding="UTF-8-BOM")
# demog <- read.csv("demographics.csv",fileEncoding="UTF-8-BOM")
load(here::here(".","migr.Rdata"))
load(here::here(".","demog.Rdata"))</pre>
```

### 2 DATA EXPLORATION BY COUNTRY

### 2.a Preliminary check on demog and migr

```
## 3
                               bachelor
                                               CXO
                                                        Retail & Consumer Products
## 4
              4
                                                             Technology - Hardware
                                 master
                                            Entry
## 5
              5
                                 master
                                            Senior Government/Education/Non-profit
##
          POSITION_FUNCTION
## 1 Information Technology
       Business Development
       Business Development
## 4 Information Technology
## 5
                  Education
str(demog)
## 'data.frame':
                    475316 obs. of 5 variables:
   $ NEW MEM ID
                              : int 1 2 3 4 5 6 7 8 9 10 ...
   \ HIGHEST_DEGREE_OBTAINED : Factor \ w/ 4 levels "associate", "bachelor", ...: 3 3 2 4 4 2 2 2 4 3 ....
                              : Factor w/ 11 levels "CXO", "Director", ...: 3 6 1 3 7 11 7 1 4 4 ...
## $ SENIORITY
## $ EMPLOYER_INDUSTRY_SECTOR: Factor w/ 14 levels "Aero/Auto/Transport",..: 3 2 10 12 4 14 7 7 4 4 ...
   $ POSITION_FUNCTION
                              : Factor w/ 26 levels "Accounting", "Administrative",..: 13 4 4 13 7 18 16
summary(demog)
                     #see some summary statistics of each column
##
      NEW_MEM_ID
                     HIGHEST_DEGREE_OBTAINED
                                                 SENIORITY
                     associate: 81072
##
   Min. :
                                              Entry
                                                      :220187
                     bachelor:252952
   1st Qu.:118830
                                              Senior :146986
   Median :237658
                     doctor
                              : 40502
                                              Manager: 46279
##
  Mean
           :237658
                              :100790
                                              Training: 22047
                     master
   3rd Qu.:356487
                                              Director: 21093
## Max.
           :475316
                                                      : 7884
##
                                              (Other): 10840
##
                       EMPLOYER_INDUSTRY_SECTOR
                                                              POSITION FUNCTION
  Government/Education/Non-profit: 85999
                                                 Engineering
                                                                       : 53792
## Technology - Software
                                                                        : 41195
                                   : 65725
                                                 Education
## Healthcare & Pharmaceutical
                                   : 63281
                                                 Sales
                                                                        : 39617
## Professional Services
                                    : 60623
                                                 Operations
                                                                        : 36840
## Financial Services & Insurance : 48297
                                                 Research
                                                                        : 31635
## Retail & Consumer Products
                                   : 36494
                                                 Information Technology: 31435
## (Other)
                                    :114897
                                                 (Other)
                                                                       :240802
   sapply(demog, class) # get class of all columns
    names(migr)
                     #see all header (column) names
migr[1:5,]
                    # Indexing (1st to 5 th rows only)
     NEW_MEM_ID WEEK_BEGINNING SOURCE_COUNTRY
                                                            SOURCE_REGION
##
## 1
                     1/31/2016 United States
                                                   San Francisco Bay Area
              1
## 2
              2
                     9/18/2016 United States Greater New York City Area
## 3
              3
                     5/22/2016 United States
                                                   San Francisco Bay Area
## 4
              4
                     7/24/2016 United States
                                                     Greater Detroit Area
## 5
              5
                     1/24/2016 United States Greater New York City Area
     DESTINATION_COUNTRY
                                DESTINATION_REGION
##
## 1
           United States Greater Philadelphia Area
## 2
                            London, United Kingdom
          United Kingdom
## 3
           United States
                            Dallas/Fort Worth Area
## 4
           United States
                               Greater Boston Area
## 5
           United States
                            San Francisco Bay Area
```

```
str(migr)
                    475316 obs. of 6 variables:
##
  'data.frame':
   $ NEW MEM ID
                         : int 1 2 3 4 5 6 7 8 9 10 ...
   $ WEEK_BEGINNING
                         : Factor w/ 53 levels "1/10/2016","1/17/2016",...: 5 51 34 43 3 45 52 31 46 46
                         : Factor w/ 3 levels "Australia", "United Kingdom",...: 3 3 3 3 3 3 3 3 3 ...
##
   $ SOURCE_COUNTRY
##
   $ SOURCE_REGION
                         : Factor w/ 347 levels "Aberdeen, United Kingdom",..: 272 126 272 118 126 333
   $ DESTINATION_COUNTRY: Factor w/ 3 levels "Australia", "United Kingdom",..: 3 2 3 3 3 3 3 3 3 ...
##
   $ DESTINATION_REGION : Factor w/ 282 levels "Abilene, Texas Area",..: 106 157 61 93 222 168 104 11
summary(migr)
                    #see some summary statistics of each column
##
     NEW MEM ID
                       WEEK BEGINNING
                                               SOURCE COUNTRY
##
   Min.
         :
                1
                     7/31/2016: 11460
                                        Australia
                                                      : 8902
   1st Qu.:118830
                     8/21/2016: 11433
                                        United Kingdom: 36615
   Median :237658
                     8/14/2016: 11384
                                        United States: 429799
##
##
   Mean
           :237658
                     9/11/2016: 11184
   3rd Qu.:356487
##
                     8/28/2016: 11182
##
   Max.
           :475316
                     8/7/2016 : 10916
##
                     (Other) :407757
##
                       SOURCE_REGION
                                            DESTINATION_COUNTRY
##
  Greater New York City Area: 37000
                                        Australia
                                                      : 8647
                                        United Kingdom: 36199
## Greater Los Angeles Area
                             : 23070
##
   San Francisco Bay Area
                              : 22643
                                        United States: 430470
  Washington D.C. Metro Area: 19744
##
  Greater Chicago Area
                              : 18521
##
   Greater Boston Area
                              : 16898
##
    (Other)
                              :337440
##
                     DESTINATION_REGION
  Greater New York City Area: 38088
## San Francisco Bay Area
                              : 36707
## Washington D.C. Metro Area: 25549
## Greater Los Angeles Area : 23362
## London, United Kingdom
                              : 20136
   Greater Boston Area
                              : 17909
##
   (Other)
                              :313565
  sapply(migr, class)
                         # get class of all columns
```

- Data contains 347 origin regions and only 282 destinations
- All Linkedin members (in data) have some tertiary education degree,  $\sim 50\%$  are Entry level
- Linkedin members (in data) are distributed in 14 sectors

```
both <- left_join(demog,migr, by="NEW_MEM_ID")
```

Merge the 2 tables

### 2.b Frequencies and Proportions

I'm interested in studying members distribution across categorical variables according to origin country

### Percentages and Proportions of HIGHEST DEGREE across countries of origin

```
# Single variable
country <- table(both$SOURCE_COUNTRY)</pre>
# Proportions for a single variable table
prop.table(country)
# Cross table by two variables
xcountry <- xtabs(~ HIGHEST_DEGREE_OBTAINED +SOURCE_COUNTRY, both)
# xcountry
addmargins(xcountry)
# Proportions in Cross Table
prop.table(xcountry)
                                  # proportion to total
prop.table(xcountry, margin = 1) # proportion to row sum (DEGREE)
prop.table(xcountry, margin = 2) # proportion to column sum (ORIGIN COUNTRY)
# Stratified Table
## 3rd variable as stratified variable
xcountry2 <- xtabs(~ HIGHEST_DEGREE_OBTAINED +SENIORITY +SOURCE_COUNTRY, both)
xcountry2
## flat table
ftable(xcountry2)
```

### Proportions of HIGHEST DEGREE/Seniority/Sector/Position against Country of origin with Dplyr

```
# Prop of members in each DEGREE to SUM of Country of origin
freq_OrigDegree <- both %>%
  group_by(both[,7],both[,2]) %>%
  summarise (n = n()) \%
  mutate(freq = n / sum(n)) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
## `summarise()` has grouped output by 'both[, 7]'. You can override using the
## `.groups` argument.
freq_OrigDegree #
## # A tibble: 12 x 5
## # Groups: both[, 7] [3]
##
       `both[, 7]` `both[, 2]`
                                           n freq rel.freq
##
       <fct>
                        <fct> <int> <dbl> <chr>
## 1 Australia associate 255 0.0286 2.86% ## 2 Australia bachelor 5632 0.633 63.27% ## 3 Australia doctor 611 0.0686 6.86% ## 4 Australia master 2404 0.270 27.01%
## 5 United Kingdom associate 1312 0.0358 3.58%
## 6 United Kingdom bachelor 22107 0.604 60.38%
## 7 United Kingdom doctor
## 7 United Kingdom doctor 3533 0.0965 9.65%
## 8 United Kingdom master 9663 0.264 26.39%
## 9 United States associate 79505 0.185 18.5%
## 10 United States bachelor 225213 0.524 52.4%
## 11 United States doctor 36358 0.0846 8.46%
## 12 United States master
                                       88723 0.206 20.64%
```

```
freq_OrigSniority <- both %>%
  group_by(both[,7],both[,3]) %>%
  summarise (n = n()) \%
  mutate(freq = n / sum(n)) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
## `summarise()` has grouped output by 'both[, 7]'. You can override using the
## `.groups` argument.
freq_OrigSniority # % remarkably similar in terms of Seniority across countries of ORIGIN
## # A tibble: 31 x 5
## # Groups: both[, 7] [3]
##
      `both[, 7]` `both[, 3]`
                                      freq rel.freq
                                n
##
      <fct>
                 <fct>
                             <int>
                                      <dbl> <chr>
## 1 Australia
                 CXO
                              119 0.0134
                                           1.34%
## 2 Australia
                Director
                               323 0.0363
                                           3.63%
## 3 Australia Entry
                             3542 0.398
                                           39.79%
## 4 Australia Manager
                             1150 0.129
                                           12.92%
## 5 Australia Owner
                              80 0.00899 0.9%
## 6 Australia Partner
                               41 0.00461 0.46%
## 7 Australia Senior
                             3331 0.374
                                           37.42%
                              154 0.0173
## 8 Australia Training
                                           1.73%
## 9 Australia Unpaid
                                1 0.000112 0.01%
## 10 Australia
                              161 0.0181
                                           1.81%
## # i 21 more rows
freq OrigSector <- both %>%
  group_by(both[,7],both[,4]) %>%
  summarise (n = n()) \%
 mutate(freq = n / sum(n)) %>%
 mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
## `summarise()` has grouped output by 'both[, 7]'. You can override using the
## `.groups` argument.
freq_OrigSector # % remarkably similar in terms of sector across countries
## # A tibble: 42 x 5
## # Groups: both[, 7] [3]
##
      `both[, 7]` `both[, 4]`
                                                        freq rel.freq
##
      <fct>
                 <fct>
                                                <int> <dbl> <chr>
## 1 Australia Aero/Auto/Transport
                                                  357 0.0401 4.01%
## 2 Australia Architecture & Engineering
                                                  805 0.0904 9.04%
## 3 Australia Financial Services & Insurance
                                                  926 0.104 10.4%
## 4 Australia Government/Education/Non-profit 1716 0.193 19.28%
## 5 Australia Healthcare & Pharmaceutical
                                                  723 0.0812 8.12%
## 6 Australia Manufacturing/Industrial
                                                  372 0.0418 4.18%
## 7 Australia Media & Entertainment
                                                  506 0.0568 5.68%
## 8 Australia Oil & Energy
                                                  251 0.0282 2.82%
## 9 Australia Professional Services
                                                 1481 0.166 16.64%
## 10 Australia Retail & Consumer Products
                                                  504 0.0566 5.66%
## # i 32 more rows
freq_OrigPosition <- both %>%
group_by(both[,7],both[,5]) %>%
```

```
summarise (n = n()) \%
 mutate(freq = n / sum(n)) %>%
 mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
## `summarise()` has grouped output by 'both[, 7]'. You can override using the
## `.groups` argument.
freq_OrigPosition # % remarkably similar in terms of position across countries
## # A tibble: 78 x 5
## # Groups: both[, 7] [3]
      `both[, 7]` `both[, 5]`
##
                                                      freq rel.freq
##
      <fct>
                 <fct>
                                              <int> <dbl> <chr>
## 1 Australia Accounting
                                                208 0.0234 2.34%
## 2 Australia Administrative
                                                162 0.0182 1.82%
## 3 Australia Arts and Design
                                                293 0.0329 3.29%
## 4 Australia Business Development
                                                663 0.0745 7.45%
## 5 Australia Community and Social Services 439 0.0493 4.93%
## 6 Australia Consulting
                                                247 0.0277 2.77%
## 7 Australia
                 Education
                                                521 0.0585 5.85%
## 8 Australia
                 Engineering
                                                830 0.0932 9.32%
## 9 Australia
                 Entrepreneurship
                                                112 0.0126 1.26%
## 10 Australia
                                                508 0.0571 5.71%
                 Finance
## # i 68 more rows
```

- US has a significantly higher # of Associates leaving (18% vs 3% and 4%)
- Proportions seem remarkably similar in terms of Seniority / Sector / Position across countries of ORIGIN
- At the country level there are no big differences... probably makes more sense looking at city or internally
- Wonder if this is a subset of real Linkedin members or if there are particular similarities in the English-speaking countries

### Percentages and Proportions - Seniority/Sector/Position against Country of DESTINATION-with Dplyr

I do the same analysis but looking at DESTINATION \* Very similar results as per Origin

```
# prop DEGREE by country orf destin
freq_DestDegree <- both %>%
  group_by(both[,9],both[,2]) %>%
  summarise (n = n()) %>%
  mutate(freq = n / sum(n)) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
freq_DestDegree # US has a significantly higher # of Associates leaving (18% vs 3% and 4%)
# prop SENIORITY by country orf destin
freq_DestSniority <- both %>%
  group_by(both[,9],both[,3]) %>%
  summarise (n = n()) %>%
  mutate(freq = n / sum(n)) %>%
  mutate(freq = paste0(round(100 * n/sum(n), 2), "%"))
freq_DestSniority # % remarkably similar in terms of Seniority across countries
# prop SECTOR by country orf destin
```

```
freq_DestSector <- both %>%
  group_by(both[,9],both[,4]) %>%
  summarise (n = n()) \%
  mutate(freq = n / sum(n)) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
freq_DestSector # % remarkably similar in terms of sector across countries
# prop POSITION by country orf destin
freq_DestPosition <- both %>%
  group_by(both[,9],both[,5]) %>%
  summarise (n = n()) \%
  mutate(freq = n / sum(n)) %>%
  mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
freq_DestPosition # % remarkably similar in terms of position across countries
# 3-Way Frequency Table
# mytable <- table(both[,4],both[,2], both[,3])</pre>
# ftable(mytable)
```

### 3 DATA EXPLORATION BY CITY

```
# create origin table
origin <- both %>% select(id=NEW_MEM_ID, degree=HIGHEST_DEGREE_OBTAINED, seniority=SENIORITY, sector=EM
# create destination table
destination <- both %>% select(id=NEW_MEM_ID, degree=HIGHEST_DEGREE_OBTAINED, seniority=SENIORITY, sector=EM
```

interim manipulation

### 3.1 Top 10 cities (US)

```
# Aggregate N flow (OUT) by City
library (knitr)
library(kableExtra)
aggreOrig <- origin %>%
 group_by(city0) %>%
 summarize(NumOutflow= n()) %>%
 mutate(freq = NumOutflow / sum(NumOutflow)) %>%
 arrange(desc(NumOutflow))
# Top 10 ORIGIN cities
aggreOrig_short <- aggreOrig[1:10,]</pre>
kable(aggreOrig_short, #format = "html",
     caption = "Ranking of cities by Origin") %>% kable_styling(bootstrap_options = c("striped", "hov
# create destination table
destination <- both %>% select(id=NEW_MEM_ID, degree=HIGHEST_DEGREE_OBTAINED, seniority=SENIORITY, sect
# Aggregate N flow (IN) by City
library (knitr)
```

Table 1: Ranking of cities by Origin

cityO	NumOutflow	freq	rel.freq
Greater New York City Area	37000	0.0778430	7.784
Greater Los Angeles Area	23070	0.0485361	4.854
San Francisco Bay Area	22643	0.0476378	4.764
Washington D.C. Metro Area	19744	0.0415387	4.154
Greater Chicago Area	18521	0.0389657	3.897
Greater Boston Area	16898	0.0355511	3.555
Dallas/Fort Worth Area	11592	0.0243880	2.439
Greater Philadelphia Area	11407	0.0239988	2.400
Greater Atlanta Area	11092	0.0233361	2.334
London, United Kingdom	10249	0.0215625	2.156

Table 2: Ranking of cities by popular destination

cityD	NumInflow	freq	rel.freq
Greater New York City Area	38088	0.0801320	8.013
San Francisco Bay Area	36707	0.0772265	7.723
Washington D.C. Metro Area	25549	0.0537516	5.375
Greater Los Angeles Area	23362	0.0491505	4.915
London, United Kingdom	20136	0.0423634	4.236
Greater Boston Area	17909	0.0376781	3.768
Greater Chicago Area	16944	0.0356479	3.565
Dallas/Fort Worth Area	16157	0.0339921	3.399
Greater Seattle Area	15553	0.0327214	3.272
Greater Atlanta Area	14242	0.0299632	2.996

```
library(kableExtra)
aggreDest <- destination %>%
    group_by(cityD) %>%
    summarize(NumInflow= n())    %>%
    mutate(freq = NumInflow / sum(NumInflow)) %>%
    mutate(rel.freq = as.numeric(pasteO(round(100 * NumInflow/sum(NumInflow), 3))))    %>%
    arrange(desc(NumInflow))

# Top 10 DESTINATION cities
aggreDest_short <- aggreDest[1:10,]
kable(aggreDest_short, #format = "html",
    caption = "Ranking of cities by popular destination") %>% kable_styling(bootstrap_options = c("state))
```

- Intristingly, London is # 5 Origin but # 10 Destination
- -9/10 top DESTINATION are the same as top ORIGIN which suggest there is mobility, but not necessarily the top destination are places where people stay
- this can be explained by the American way of moving to and from the city of college
- those where all american !!!

Table 3: Ranking of cities by Origin

cityO	NumOutflow	freq	rel.freq
London, United Kingdom	10249	0.2799126	27.991
Manchester, United Kingdom	1170	0.0319541	3.195
Reading, United Kingdom	1002	0.0273658	2.737
Twickenham, United Kingdom	990	0.0270381	2.704
Oxford, United Kingdom	978	0.0267104	2.671
Birmingham, United Kingdom	836	0.0228322	2.283
Guildford, United Kingdom	828	0.0226137	2.261
Kingston upon Thames, United Kingdom	788	0.0215212	2.152
Coventry, United Kingdom	695	0.0189813	1.898
Cambridge, United Kingdom	668	0.0182439	1.824

### 3.2 Top 10 cities (UK)

```
# Aggregate N flow (OUT) by City
library (knitr)
library(kableExtra)
# subset origin
originUK <- subset (origin , countryO == "United Kingdom")</pre>
aggreOrigUK <- originUK %>%
 group_by(city0) %>%
 summarize(NumOutflow= n()) %>%
 mutate(freq = NumOutflow / sum(NumOutflow)) %>%
 arrange(desc(NumOutflow)) #%>% left_join(origin, by="cityO")
# Top 10 ORIGIN cities
aggreOrig_shortUK <- aggreOrigUK[1:10,]</pre>
kable(aggreOrig_shortUK, #format = "html",
     caption = "Ranking of cities by Origin") %>% kable_styling(bootstrap_options = c("striped", "hov
# -----#
# subset destination
destinationUK <- subset (destination , countryD == "United Kingdom")</pre>
# Aggregate N flow (IN) by City
library (knitr)
library(kableExtra)
aggreDestUK <- destinationUK %>%
 group_by(cityD) %>%
 summarize(NumInflow= n()) %>%
 mutate(freq = NumInflow / sum(NumInflow)) %>%
 arrange(desc(NumInflow))
# Top 10 DESTINATION cities
aggreDest_shortUK <- aggreDestUK[1:10,]</pre>
```

Table 4: Ranking of cities by popular destination

cityD	NumInflow	freq	rel.freq
London, United Kingdom	20136	0.5562585	55.626
Manchester, United Kingdom	1859	0.0513550	5.136
Birmingham, United Kingdom	949	0.0262162	2.622
Edinburgh, United Kingdom	803	0.0221829	2.218
Bristol, United Kingdom	754	0.0208293	2.083
Reading, United Kingdom	754	0.0208293	2.083
Cambridge, United Kingdom	719	0.0198624	1.986
Leeds, United Kingdom	695	0.0191994	1.920
Glasgow, United Kingdom	682	0.0188403	1.884
Oxford, United Kingdom	554	0.0153043	1.530

 Contrary to widespread mobility in US, London is origin of 28% of migrants and the Destination for 55% of them

### 3.3 Top 10 cities (Austr)

```
# Aggregate N flow (OUT) by City
library (knitr)
library(kableExtra)
# subset origin
originAustr <- subset (origin , countryO == "Australia")</pre>
aggreOrigAustr <- originAustr %>%
 group_by(city0) %>%
 summarize(NumOutflow= n()) %>%
 mutate(freq = NumOutflow / sum(NumOutflow)) %>%
 arrange(desc(NumOutflow)) #%>% left_join(origin, by="cityO")
# Top 10 ORIGIN cities
aggreOrig_shortAustr <- aggreOrigAustr[1:10,]</pre>
kable(aggreOrig_shortAustr, #format = "html",
     caption = "Ranking of cities by Origin") %>% kable_styling(bootstrap_options = c("striped", "hov
# -----#
# subset destination
destinationAustr <- subset (destination , countryD == "Australia")</pre>
# Aggregate N flow (IN) by City
library (knitr)
library(kableExtra)
aggreDestAustr <- destinationAustr %>%
```

Table 5: Ranking of cities by Origin

cityO	NumOutflow	freq	rel.freq
Sydney Area, Australia	3209	0.3604808	36.048
Brisbane Area, Australia	1995	0.2241069	22.411
Perth Area, Australia	1014	0.1139070	11.391
Adelaide Area, Australia	611	0.0686363	6.864
Canberra Area, Australia	556	0.0624579	6.246
Queensland, Australia	468	0.0525725	5.257
New South Wales, Australia	357	0.0401033	4.010
Newcastle Area, Australia	216	0.0242642	2.426
Western Australia, Australia	103	0.0115704	1.157
Toowoomba Area, Australia	74	0.0083127	0.831

Table 6: Ranking of cities by popular destination

cityD	NumInflow	freq	rel.freq
Sydney Area, Australia	3885	0.4492888	44.929
Brisbane Area, Australia	2046	0.2366139	23.661
Canberra Area, Australia	674	0.0779461	7.795
Perth Area, Australia	532	0.0615242	6.152
Queensland, Australia	452	0.0522725	5.227
New South Wales, Australia	393	0.0454493	4.545
Adelaide Area, Australia	306	0.0353880	3.539
Newcastle Area, Australia	180	0.0208165	2.082
Western Australia, Australia	110	0.0127212	1.272
Toowoomba Area, Australia	69	0.0079796	0.798

- Similar to UK, in Australiam Sydney is the origin of 36% of migrants and the Destination for 50% of them

### 3.4 Plots of top cities

```
# Adding some variables for plots
aggreByCity <- full_join(aggreDest,aggreOrig, by = c("cityD" = "cityO"))
aggreByCity[c("NumInflow", "NumOutflow")][is.na(aggreByCity[c("NumInflow", "NumOutflow")])] <- 0
aggreByCity <- aggreByCity %>%
  select(-freq.x,-rel.freq.x, -freq.y, -rel.freq.y) %>% # get rid of meeaningless
```

```
mutate (NetFlow= NumInflow -NumOutflow) %>% # Net
mutate (NegOutFlow= -(NumOutflow)) %>% # neg sign
mutate (Sign = ifelse(NetFlow > 0, "Positive", "Negative")) %>%
mutate (colour= ifelse(NetFlow > 0, "positive", "negative")) %>% mutate (city_copy = cityD) %>%
separate(city_copy, into = c("city_only", "metro area"), sep = ",")
summary(aggreByCity)
```

JOIN the AGGREGATE by CITY to have Net flows in the same table (by City)

```
names(aggreByCity)[1]<-"city"</pre>
names(migr)[4]<-"city"</pre>
\# city_country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", "SOURCE_REGION")) %>% \# #select(city,country <-full_join(aggreByCity, migr, by = c("city", migr, by = c("city",
city_country <-full_join(aggreByCity, migr, by = "city") %>%
    select(city, country=DESTINATION_COUNTRY) %>%
    distinct () %>% # need the dup flag
    mutate(dupli = ifelse((city == "Greater New York City Area" | city == "San Francisco Bay Area" | city == "W
    city =="Greater Los Angeles Area" | city == "Greater Boston Area" | city == "Greater Chicago Area" |
    city =="Dallas/Fort Worth Area" |city =="Greater Seattle Area" |city =="San Francisco Bay Area") & co
    mutate(dupli2 = ifelse((city =="London, United Kingdom") & country!="United kindom", "dup", "")) %>%
    mutate(dupli3 = ifelse((city =="Sydney Area, Australia") & country!="Australia", "dup", "")) %>% # ne
    mutate(dupli4 = ifelse((city =="Perth Area, Australia") & country!="Australia", "dup", "")) %>% # nee
    mutate(dupli5 = ifelse((city =="Miami/Fort Lauderdale Area") & country!="United States", "dup", ""))
    mutate(dupli6 = ifelse((city =="Brisbane Area, Australia") & country!="Australia", "dup", ""))
city_country <- subset(city_country, city_country$dupli!="dup" & city_country$dupli2!="dup" & city_country
newRow <- data.frame(city ="London, United Kingdom", country ="United Kingdom")
city_country <- rbind(city_country,newRow)</pre>
#city_country <- rbind(city_country, c("London, United Kingdom", "United kindom"))</pre>
names(aggreByCity)[1]<-"cityD"</pre>
```

### interim

Major 30 (World - mostly US) cities TO people are migrating

```
names(aggreByCity)[1] <- "city"

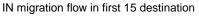
# 1) In Flow in Top DESTINATION
Top_in <- aggreByCity %>% top_n(30, NumInflow)
   Top_in$city = with(Top_in, reorder(city, NumInflow)) # reorder Levels by Var
```

```
Top_in <- ggplot(data = Top_in,aes(city, NumInflow)) +
  geom_bar(stat = "identity", position="identity", fill = "steelblue") +
  geom_hline(yintercept=10000, color = "black", size=0.5) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" labs(title="IN migration flow in first 15 destination")

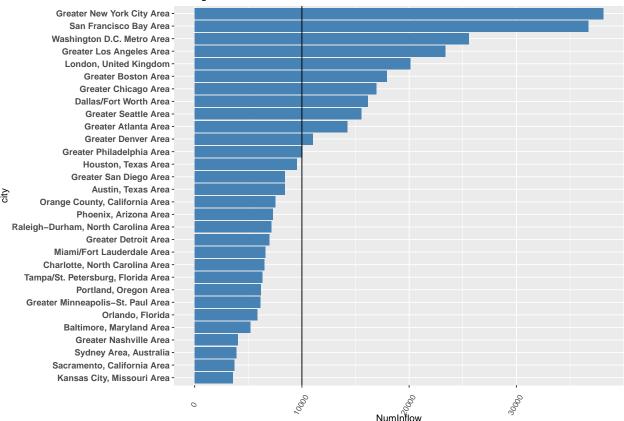
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.</pre>
```

Top\_in + coord\_flip()

## generated.



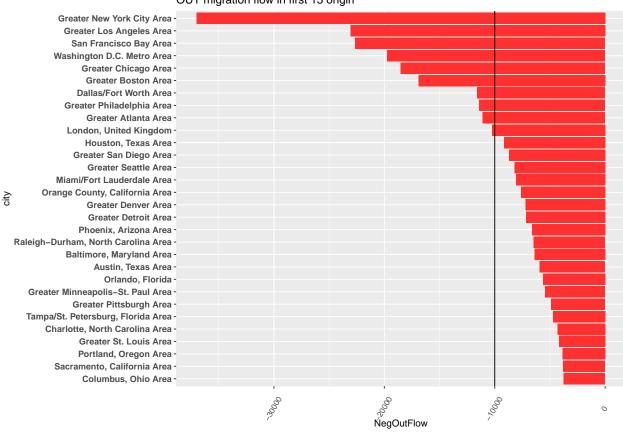
## Call `lifecycle::last\_lifecycle\_warnings()` to see where this warning was



```
# 2) Out Flow in Top ORIGIN
Top_out <- aggreByCity %>% top_n(30, NumOutflow)
  Top_out$city = with(Top_out, reorder(city,NumOutflow)) # reorder Levels by Var

Top_out <- ggplot(data = Top_out,aes(city, NegOutFlow)) +
  geom_bar(stat = "identity", position="identity", fill = "firebrick1") +
  geom_hline(yintercept=-10000, color = "black", size=0.5) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" labs(title="OUT migration flow in first 15 origin")</pre>
Top_out + coord_flip()
```





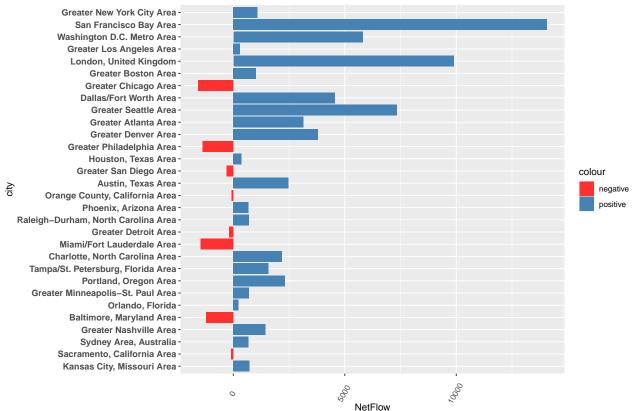
```
# plot side by side
# library(gridExtra)
# grid.arrange(in_flip, out_flip, ncol=2)

# 3.a) NET flow in Top DESTINATION
Top_net <- aggreByCity %>% top_n(30, NumInflow)
    Top_net$city = with(Top_net, reorder(city,NumInflow)) # reorder Levels by Var

Top_net <- ggplot(data = Top_net,aes(city, NetFlow)) +
    geom_bar(stat = "identity", position="identity",aes(fill = colour)) +
    theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" scale_fill_manual(values=c(positive="steelblue",negative="firebrick1")) +
    labs(title="NET migration flow in first 25 destination", subtitle="(ordered by destination)")

Top_net + coord_flip()</pre>
```

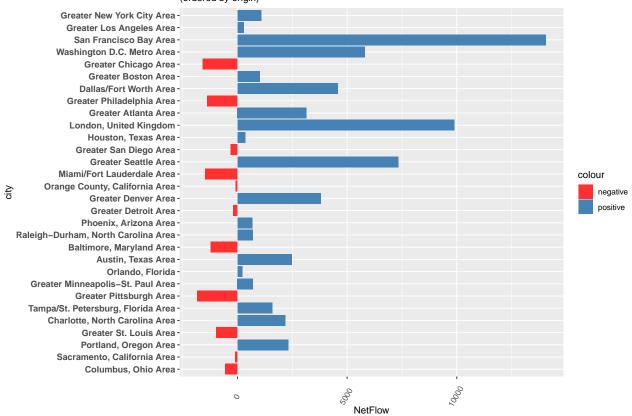
### NET migration flow in first 25 destination (ordered by destination)



```
# 3.b) NET flow in Top ORIGIN
Top_net <- aggreByCity %>% top_n(30, NumOutflow)
  Top_net$city = with(Top_net, reorder(city,NumOutflow)) # reorder Levels by Var

Top_net <- ggplot(data = Top_net,aes(city, NetFlow)) +
  geom_bar(stat = "identity", position="identity",aes(fill = colour)) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" scale_fill_manual(values=c(positive="steelblue",negative="firebrick1")) +
  labs(title="NET migration flow in first 25 origin", subtitle="(ordered by origin)")
Top_net + coord_flip()</pre>
```

### NET migration flow in first 25 origin (ordered by origin)



```
# all american
# lots of leaving in 2016 - especially in NY

# add country to aggreByCity
aggreByCity2 <- left_join(aggreByCity,city_country,by = "city")

# x[c("a", "b")][is.na(x[c("a", "b")])] <- 0
aggreByCity2[c("NumInflow", "NumOutflow")][is.na(aggreByCity2[c("NumInflow", "NumOutflow")])] <- 0</pre>
```

### Major 20 (UK) cities TO / FROM / NET migration

```
# 1) In Flow in Top DESTINATION

aggreByCityUK <- aggreByCity2 %>%
  filter (country == "United Kingdom")

Top_inUK <- aggreByCityUK %>%
  top_n(30, NumInflow)

Top_inUK$city = with(Top_inUK, reorder(city,NumInflow)) # reorder Levels by Var

Top_inUK <- ggplot(data = Top_inUK,aes(city, NumInflow)) +
  geom_bar(stat = "identity", position="identity", fill = "steelblue") +
  geom_hline(yintercept=10000, color = "black", size=0.5) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" labs(title="IN migration flow in first 15 destination")</pre>
```

```
Top_inUK + coord_flip()
```

### IN migration flow in first 15 destination

```
London, United Kingdom -
Manchester, United Kingdom -
Birmingham, United Kingdom -
Edinburgh, United Kingdom -
Reading, United Kingdom -
Reading, United Kingdom -
Reading, United Kingdom -
Cambridge, United Kingdom -
Leeds, United Kingdom -
Glasgow, United Kingdom -
Oxford, United Kingdom -
Kingston upon Thames, United Kingdom -
Guildford, United Kingdom -
Guildford, United Kingdom -
Slough, United Kingdom -
Slough, United Kingdom -
Coventry, United Kingdom -
Harrow, United Kingdom -
Harrow, United Kingdom -
Harrow, United Kingdom -
Harrow, United Kingdom -
Guithon, United Kingdom -
Harrow, United Kingdom -
Harrow, United Kingdom -
Cardiff, United Kingdom -
Cardiff, United Kingdom -
Romford, United Kingdom -
Ro
```

```
# 2) Out Flow in Top ORIGIN
Top_outUK <- aggreByCityUK %>%
  filter (country == "United Kingdom") %>% # filter by country = UK
  top_n(30, NumOutflow)
  Top_outUK$city = with(Top_outUK, reorder(city,NumOutflow)) # reorder Levels by Var

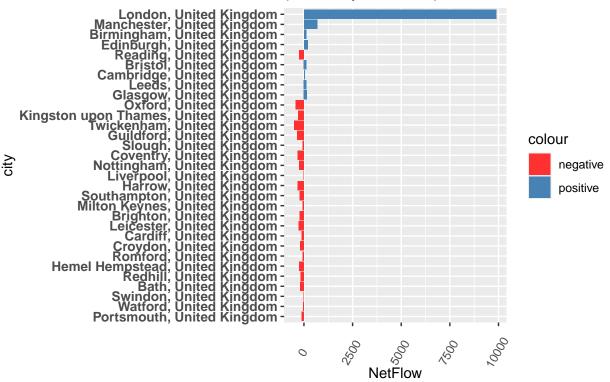
Top_outUK <- ggplot(data = Top_outUK,aes(city, NegOutFlow)) +
  geom_bar(stat = "identity", position="identity", fill = "firebrick1") +
  geom_hline(yintercept=-10000, color = "black", size=0.5) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" labs(title="OUT migration flow in first 15 origin")</pre>
Top_outUK + coord_flip()
```

### OUT migration flow in first 15 origin

```
London, United Kingdom -
Manchester, United Kingdom -
Reading, United Kingdom -
Twickenham, United Kingdom -
Oxford, United Kingdom -
Guildford, United Kingdom -
Guildford, United Kingdom -
Kingston upon Thames, United Kingdom -
Coventry, United Kingdom -
Cambridge, United Kingdom -
Bristol, United Kingdom -
Edinburgh, United Kingdom -
Nottingham, United Kingdom -
Harrow, United Kingdom -
Southall, United Kingdom -
Sheffield, United Kingdom -
Sheffield, United Kingdom -
Glasgow, United Kingdom -
Sheffield, United Kingdom -
Slough, United Kingdom -
Slough, United Kingdom -
Brighton, United Kingdom -
Groydon, United Kingdom -
Hemel Hempstead, United Kingdom -
Groydon, United Kingdom -
Hemel Hempstead, United Kingdom -
Slough, United Kingdom -
Aberdeen, United Kingdom -
Slough, United Kingdom -
Aberdeen, United Kingdom -
Stockport, United Kingdom -
Stockport, United Kingdom -
Milton Keynes, United Kingdom -
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              NegOutFlow
```

```
# 3.a) NET flow in Top DESTINATION
Top_netUK <- aggreByCityUK %>%
   filter (country == "United Kingdom") %>% # filter by country = UK
  top_n(30, NumInflow)
  Top_netUK$city = with(Top_netUK, reorder(city, NumInflow)) # reorder Levels by Var
Top_netUK <- ggplot(data = Top_netUK,aes(city, NetFlow)) +</pre>
  geom_bar(stat = "identity", position="identity",aes(fill = colour)) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10, face="bold"
  scale_fill_manual(values=c(positive="steelblue",negative="firebrick1")) +
  labs(title="NET migration flow in first 25 destination", subtitle="(ordered by destination)")
Top netUK + coord flip()
```

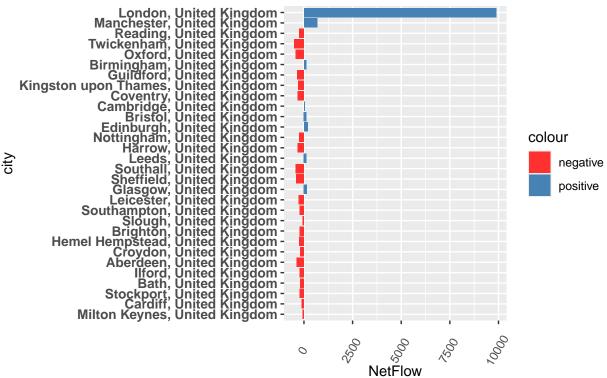
# NET migration flow in first 25 destination (ordered by destination)



```
# 3.b) NET flow in Top ORIGIN
Top_netUK <- aggreByCityUK %>%
    filter (country == "United Kingdom") %>% # filter by country = UK
    top_n(30, NumOutflow)
    Top_netUK$city = with(Top_netUK, reorder(city,NumOutflow)) # reorder Levels by Var

Top_netUK <- ggplot(data = Top_netUK,aes(city, NetFlow)) +
    geom_bar(stat = "identity", position="identity",aes(fill = colour)) +
    theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" scale_fill_manual(values=c(positive="steelblue",negative="firebrick1")) +
    labs(title="NET migration flow in first 25 origin", subtitle="(ordered by origin)")
Top_netUK + coord_flip()</pre>
```

# NET migration flow in first 25 origin (ordered by origin)



### • INSIGHTs:

- Contrary to US, London is a definitive outlier

### Major 20 (AUSTRALIA) cities TO / FROM / NET migration

```
# 1) In Flow in Top DESTINATION

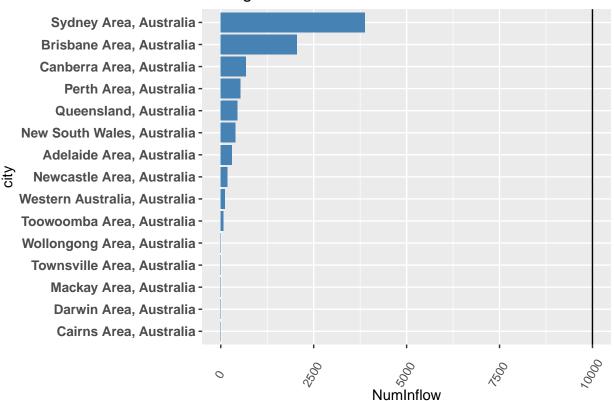
aggreByCityAustr <- aggreByCity2 %>%
  filter (country == "Australia")

Top_inAustr <- aggreByCityAustr %>%
  top_n(30, NumInflow)

Top_inAustr$city = with(Top_inAustr, reorder(city,NumInflow)) # reorder Levels by Var

Top_inAustr <- ggplot(data = Top_inAustr,aes(city, NumInflow)) +
  geom_bar(stat = "identity", position="identity", fill = "steelblue") +
  geom_hline(yintercept=10000, color = "black", size=0.5) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" labs(title="IN migration flow in first 15 destination")</pre>
Top_inAustr + coord_flip()
```

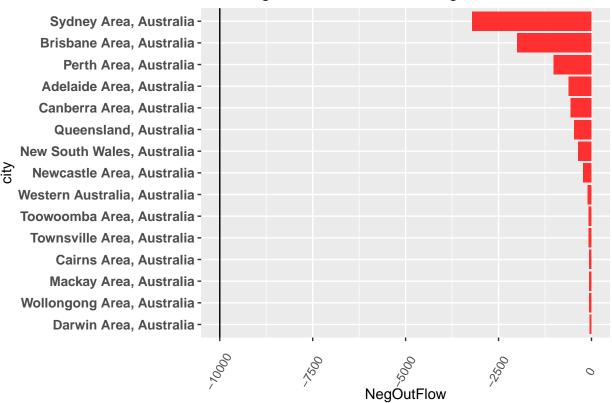
### IN migration flow in first 15 destination



```
# 2) Out Flow in Top ORIGIN
Top_outAustr <- aggreByCityAustr %>%
  filter (country == "Australia") %>% # filter by country = Austr
  top_n(30, NumOutflow)
  Top_outAustr$city = with(Top_outAustr, reorder(city,NumOutflow)) # reorder Levels by Var

Top_outAustr <- ggplot(data = Top_outAustr,aes(city, NegOutFlow)) +
  geom_bar(stat = "identity", position="identity", fill = "firebrick1") +
  geom_hline(yintercept=-10000, color = "black", size=0.5) +
  theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" labs(title="OUT migration flow in first 15 origin")</pre>
Top_outAustr + coord_flip()
```

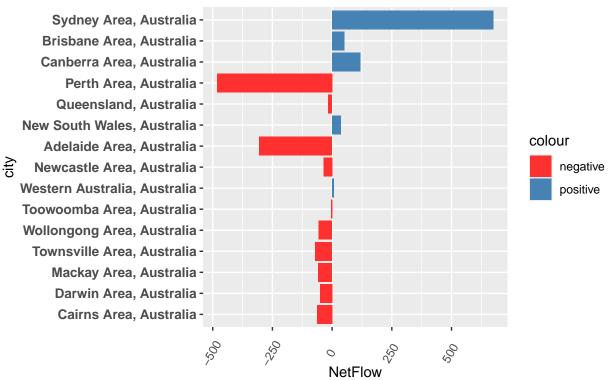
### OUT migration flow in first 15 origin



```
# 3.a) NET flow in Top DESTINATION
Top_netAustr <- aggreByCityAustr %>%
    filter (country == "Australia") %>% # filter by country = Austr
    top_n(30, NumInflow)
    Top_netAustr$city = with(Top_netAustr, reorder(city,NumInflow)) # reorder Levels by Var

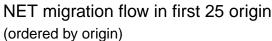
Top_netAustr <- ggplot(data = Top_netAustr,aes(city, NetFlow)) +
    geom_bar(stat = "identity", position="identity",aes(fill = colour)) +
    theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" scale_fill_manual(values=c(positive="steelblue",negative="firebrick1")) +
    labs(title="NET migration flow in first 25 destination", subtitle="(ordered by destination)")
Top_netAustr + coord_flip()</pre>
```

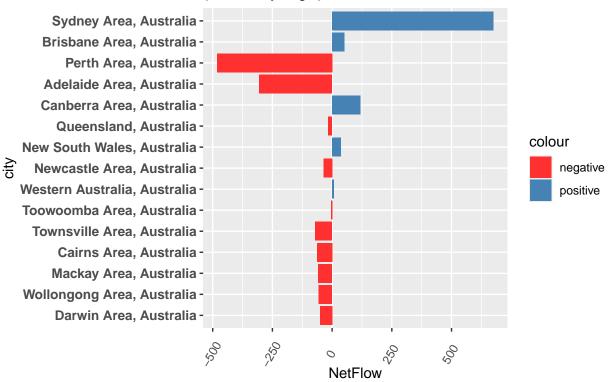
## NET migration flow in first 25 destination (ordered by destination)



```
# 3.b) NET flow in Top ORIGIN
Top_netAustr <- aggreByCityAustr %>%
    filter (country == "Australia") %>% # filter by country = Austr
    top_n(30, NumOutflow)
    Top_netAustr$city = with(Top_netAustr, reorder(city,NumOutflow)) # reorder Levels by Var

Top_netAustr <- ggplot(data = Top_netAustr,aes(city, NetFlow)) +
    geom_bar(stat = "identity", position="identity",aes(fill = colour)) +
    theme(axis.text.x = element_text(angle=60, vjust=0.3), axis.text.y = element_text(size=10,face="bold" scale_fill_manual(values=c(positive="steelblue",negative="firebrick1")) +
    labs(title="NET migration flow in first 25 origin", subtitle="(ordered by origin)")
Top_netAustr + coord_flip()</pre>
```





### 4 BIVARIATE MEASURES OF ASSOCIATION

### 4.1 INflow by city vs highest degree

Is there any relation between where they choose to go and the highest degree they have? I use plots to check distributions type of DEGREE (Y) conditional on the city of destination (X)

- I check for:
  - Existence
  - strnght
  - patterns / direction

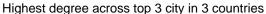
Greater New York City Area San Francisco Bay Area Washington D.C. Metro Area

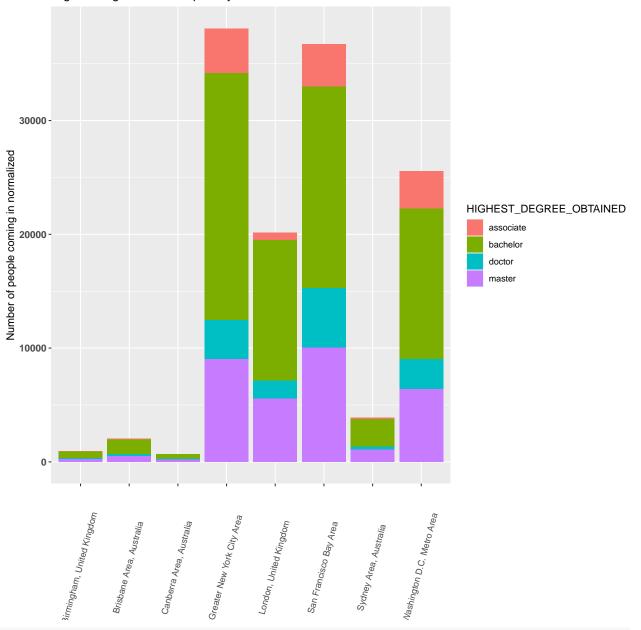
Manchester, United Kingdom London, United Kingdom Birmingham, United Kingdom

Sydney Area, Australia Brisbane Area, Australia Canberra Area, Australia

```
# 1) attempt for simplicity I select top 3 per country
#top3 <- both %>% filter(DESTINATION_REGION == "Greater New York City Area" |DESTINATION_REGION == "San It top_subs <- subset(both, (DESTINATION_REGION == 'Greater New York City Area' | DESTINATION_REGION == '# 3) attempt
# 3) attempt
# When subsetting with [ names are always matched exactly</pre>
```

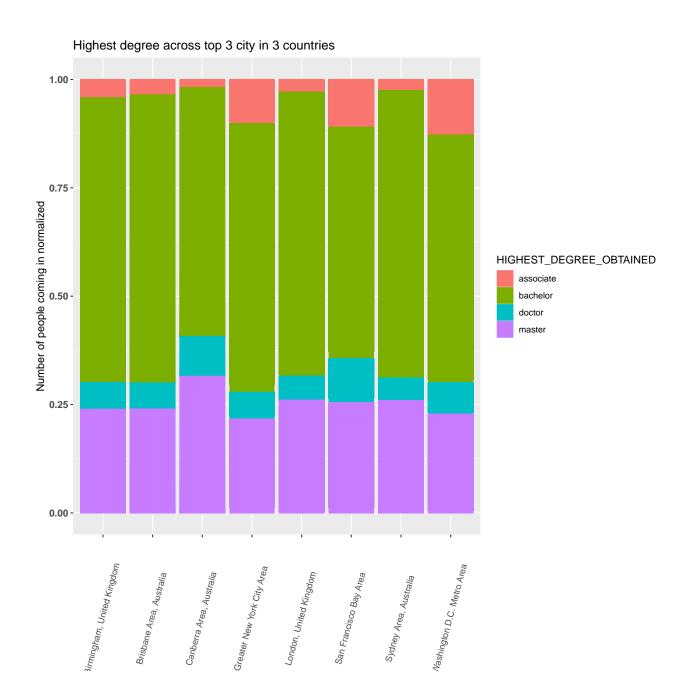
```
\# z \leftarrow c(abc = 1, def = 2)
# z[c("a", "d")]
top_dest <- c("Greater New York City Area", "San Francisco Bay Area", "Washington D.C. Metro Area",
# both_top <- both[as.character( both$DESTINATION_REGION %in% top_dest), drop = T]</pre>
# data[data$Code %in% selected,]
# both_top <- both[both$DESTINATION_REGION %in% top_dest]</pre>
# both_top <- both[as.character( both$DESTINATION_REGION %in% top_dest), drop = TRUE]
# 4) attemps
# data[data$Code == "A" | data$Code == "B", ]
top3cit <- both[both$DESTINATION_REGION == "Greater New York City Area" | both$DESTINATION_REGION == "S
# 5) attemps
# top_dest <- c("Greater New York City Area", "San Francisco Bay Area", "Washington D.C. Metro Area"
# top3cit_2 <- both[both$DESTINATION_REGION %in% top_dest, , drop =TRUE ]</pre>
# mutate (Sign = ifelse(NetFlow > 0, "Positive", "Negative"))
# Explore
# mosaicplot(table(top3cit$DESTINATION_REGION, top3cit$HIGHEST_DEGREE_OBTAINED), ylab = "Political Part
# qplot
qplot(x = DESTINATION_REGION, data = top3cit, fill = HIGHEST_DEGREE_OBTAINED, geom = "bar") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10, face="bold")
 labs(title="Highest degree across top 3 city in 3 countries", x="", y="Number of people coming in no
## Warning: `qplot()` was deprecated in ggplot2 3.4.0.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```





```
# ggplot
#ggplot(data = Best_out, aes(cityD, NegOutFlow)) +
# geom_bar(stat = "identity", position="identity", fill = "firebrick1") +
# geom_hline(yintercept=-10000, color = "black", size=0.5) +
# theme(axis.text.x = element_text(angle=60, vjust=0.3)) +
# labs(title="OUT migration flow in first 15 destination")

ggplot(top3cit, aes(x=DESTINATION_REGION, y=NEW_MEM_ID, fill=HIGHEST_DEGREE_OBTAINED)) +
geom_bar(aes(colour = HIGHEST_DEGREE_OBTAINED), stat="identity", position = "fill") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10, face="bold" labs(title="Highest degree across top 3 city in 3 countries", x="", y="Number of people coming in no.
```



- Intuitively, it would seem San Francisco (follwed by Canberra) attracts the highest amount of doctors (Canberra also the highest group with master)
- $-\,$  NY, San Francisco and Washington DC seem to receive many with "Associate" level: either young people go tehre to look for tehir first job

```
# cramer v degree X CITY OF DESTINATION (top 3)
x<- top3cit$DESTINATION_REGION
y<- top3cit$HIGHEST_DEGREE_OBTAINED

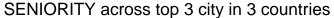
cv.test = function(x,y) {
   CV = sqrt(chisq.test(x, y, correct=FALSE)$statistic /
        (length(x) * (min(length(unique(x)),length(unique(y))) - 1)))
   print.noquote("Cramér V / Phi:")</pre>
```

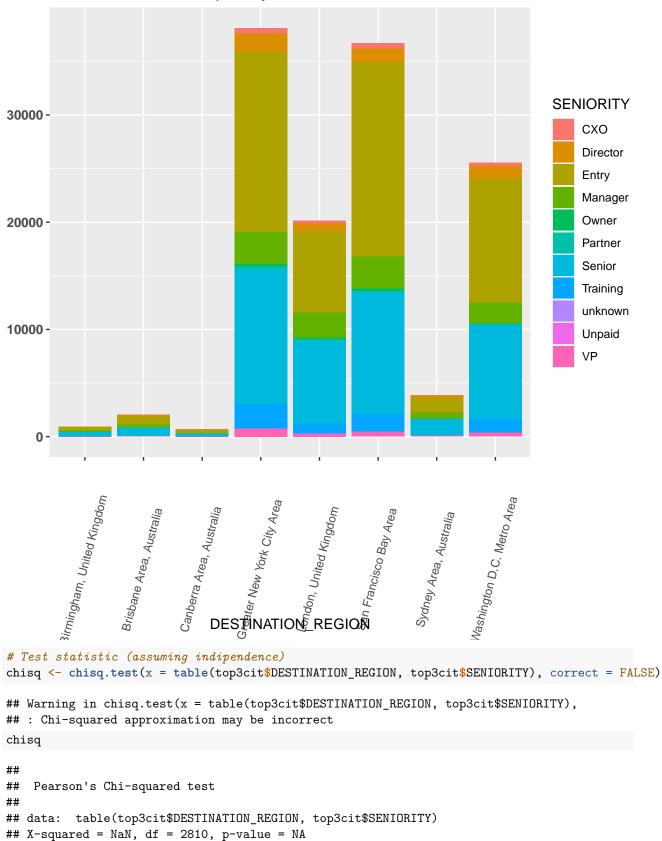
```
return(as.numeric(CV))
}
with(top3cit, cv.test(x, y)) # [1] Cramér V / Phi: 0.09052046

## [1] Cramér V / Phi:
## [1] 0.09052046

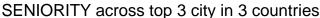
# mosaicplot(table(top3cit$DESTINATION_REGION, top3cit$SENIORITY), ylab = "Political Party", xlab = "Ta"

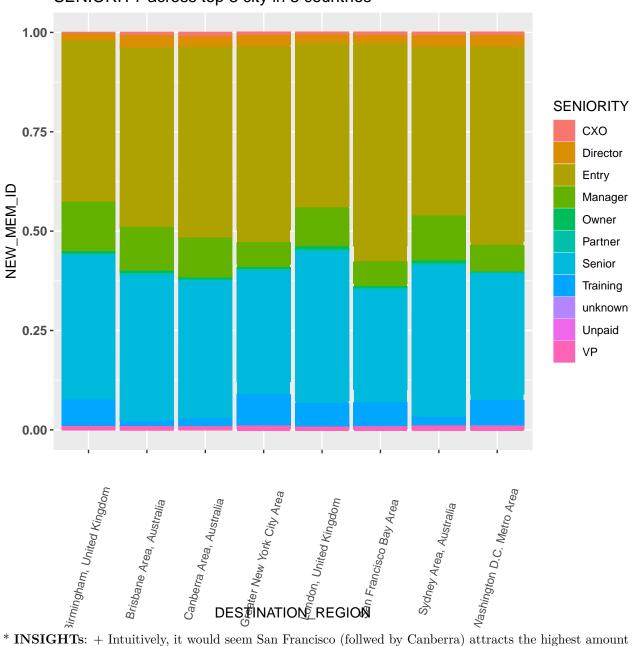
# qplot
qplot(x = DESTINATION_REGION, data = top3cit, fill = SENIORITY, geom = "bar") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10,face="bold")
labs(title="SENIORITY across top 3 city in 3 countries")
```





# # ggplot ggplot(top3cit, aes(x=DESTINATION\_REGION, y=NEW\_MEM\_ID, fill=SENIORITY)) + geom\_bar(aes(colour =SENIOR theme(axis.text.x = element\_text(angle=75, vjust=0.3), axis.text.y = element\_text(size=10,face="bold") labs(title="SENIORITY across top 3 city in 3 countries")



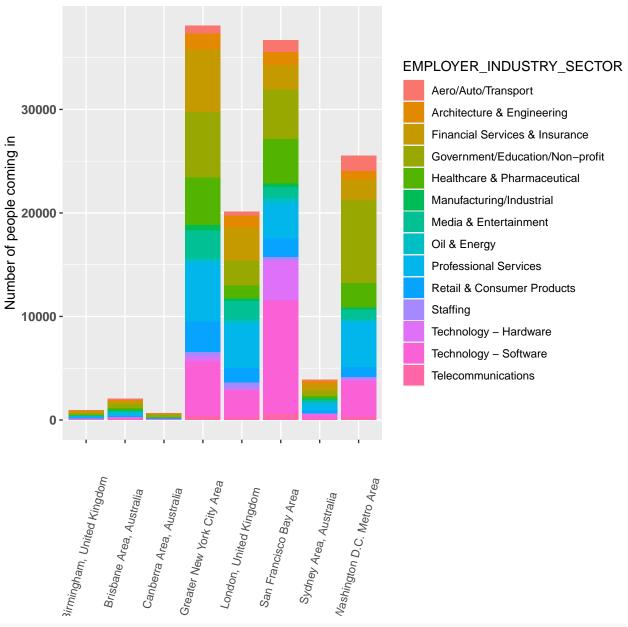


\* INSIGHTs: + Intuitively, it would seem San Francisco (follwed by Canberra) attracts the highest amount of doctors (Canberra also the highest group with master) + NY, San Francisco and Washington DC seem to receive many with "Associate" level: either young people go tehre to look for tehir first job

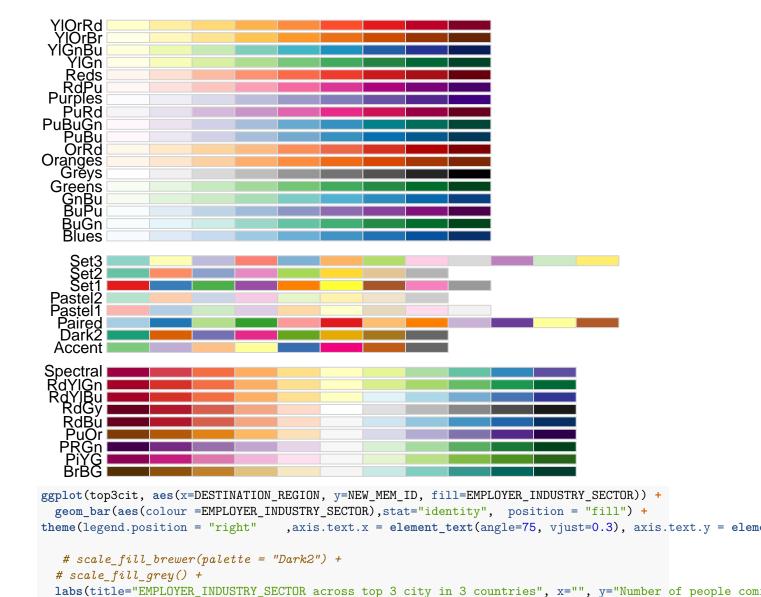
```
# cramer v SENIORITY X CITY OF DESTINATION (top 3)
x<- top3cit$DESTINATION_REGION
y<- top3cit$SENIORITY

cv.test = function(x,y) {</pre>
```

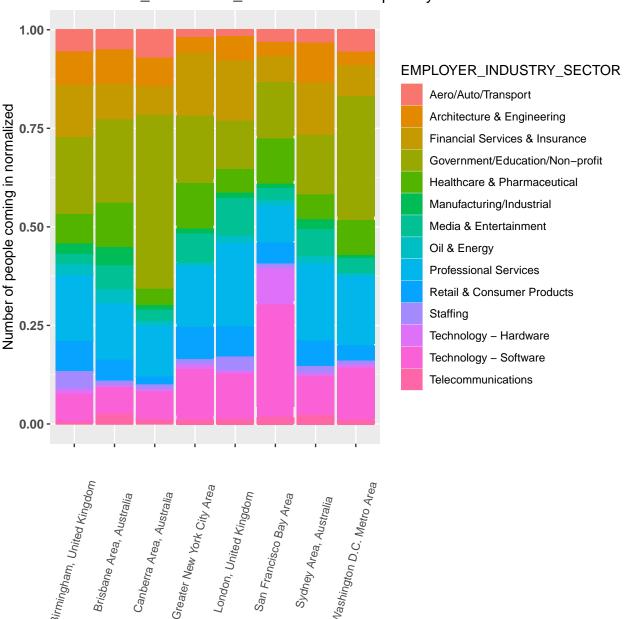




# ggplot
library(RColorBrewer)
display.brewer.all()







- Intuitively, share of immigratus by sector seems to vary a lot in different cities
- Extremely high number in Govv/ Educ/ Non Profit in Canberra & Washington
- Extremely high number in Software + Hardware Technology in San Francisco
- Extremely high number in Govv/ Educ/ Non Profit + Financial sErvices also in NY it would seem San Francisco (follwed by Canberra) attracts the highest amount of doctors (Canberra also the highest group with master)
- NY, San Francisco and Washington DC seem to receive many with "Associate" level: either young people go tehre to look for tehir first job

### CHECK A COUPLE OF CITIES FOR SECTOR X SEIORITY

```
freq_OrigDegree <- both %>%
 group_by(both[,7],both[,2]) %>%
 summarise (n = n()) \%
 mutate(freq = n / sum(n)) %>%
 mutate(rel.freq = paste0(round(100 * n/sum(n), 2), "%"))
## `summarise()` has grouped output by 'both[, 7]'. You can override using the
## `.groups` argument.
freq_OrigDegree # US has a significantly higher # of Associates leaving (18% vs 3% and 4%)
## # A tibble: 12 x 5
## # Groups: both[, 7] [3]
##
      `both[, 7]`
                    `both[, 2]`
                                         freq rel.freq
##
      <fct>
                    <fct>
                                 <int> <dbl> <chr>
                                   255 0.0286 2.86%
##
   1 Australia
                    associate
                                  5632 0.633 63.27%
##
   2 Australia
                    bachelor
##
  3 Australia
                    doctor
                                   611 0.0686 6.86%
## 4 Australia
                                  2404 0.270 27.01%
                    master
## 5 United Kingdom associate
                                 1312 0.0358 3.58%
## 6 United Kingdom bachelor
                                 22107 0.604 60.38%
## 7 United Kingdom doctor
                                3533 0.0965 9.65%
## 8 United Kingdom master
                                  9663 0.264 26.39%
## 9 United States associate
                                 79505 0.185 18.5%
## 10 United States bachelor
                                225213 0.524 52.4%
## 11 United States doctor
                                 36358 0.0846 8.46%
## 12 United States master
                                 88723 0.206 20.64%
```

Cramer's V a measure of association for nominal variables. Effectively it is the Pearson chi-square statistic rescaled to have values between 0 and 1, as follows:

$$\phi_c = \sqrt{\frac{\chi^2}{N * (min(ncols, nrows) - 1)}}$$

where  $X^2$  is the Pearson chi-square, nobs represents the number of observations included in the table, and where nools and nrows are the number of rows and columns in the table, respectively.

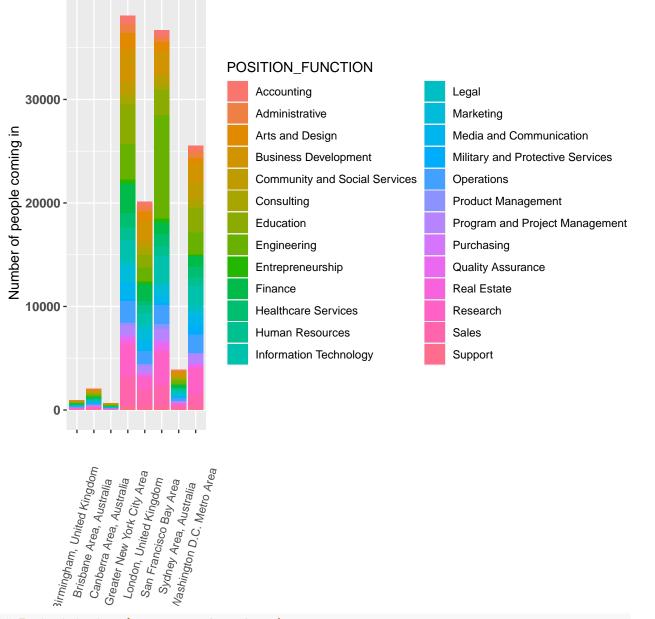
For a 2 by 2 table, of course, this is just the square root of chi-square divided by the number of observations, which is also known as the  $\phi$  coefficient.

Cramer's V varies from 0 (corresponding to no association between the variables) to 1 (complete association) and can reach 1 only when the two variables are equal to each other

```
## [1] Cramér V / Phi:
## [1] 0.1605205
# how about across all cities? (lower)
x<- both DESTINATION_REGION
y<- both SEMPLOYER_INDUSTRY_SECTOR
cv.test = function(x,y) {
 CV = sqrt(chisq.test(x, y, correct=FALSE)$statistic /
    (length(x) * (min(length(unique(x)),length(unique(y))) - 1)))
 print.noquote("Cramér V / Phi:")
 return(as.numeric(CV))
with(both, cv.test(x, y)) # [1] Cramér V / Phi: 0.1264835
## Warning in chisq.test(x, y, correct = FALSE): Chi-squared approximation may be
## incorrect
## [1] Cramér V / Phi:
## [1] 0.1264835
position
```

```
#
# mosaicplot(table(top3cit$DESTINATION_REGION, top3cit$POSITION_FUNCTION), ylab = "Political Party", xl
# qplot
qplot(x = DESTINATION_REGION, data = top3cit, fill = POSITION_FUNCTION, geom = "bar") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10,face="bold")
labs(title="POSITION_FUNCTION across top 3 city in 3 countries" , x="", y="Number of people coming in
```

## POSITION\_FUNCTION across top 3 city in 3 countries



```
# Test statistic (assuming indipendence)
chisq <- chisq.test(x = table(top3cit$DESTINATION_REGION, top3cit$POSITION_FUNCTION), correct = FALSE)

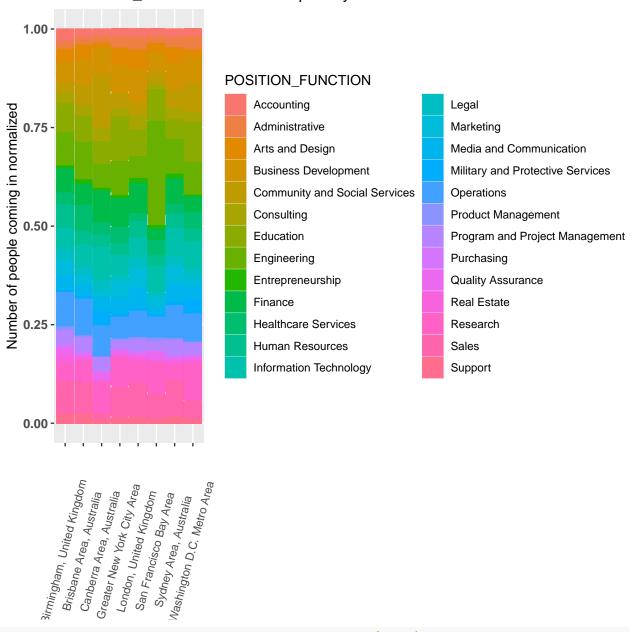
## Warning in chisq.test(x = table(top3cit$DESTINATION_REGION,
## top3cit$POSITION_FUNCTION), : Chi-squared approximation may be incorrect
chisq

##
## Pearson's Chi-squared test
##
## data: table(top3cit$DESTINATION_REGION, top3cit$POSITION_FUNCTION)</pre>
```

## X-squared = NaN, df = 7025, p-value = NA

```
# ggplot
ggplot(top3cit, aes(x=DESTINATION_REGION, y=NEW_MEM_ID, fill=POSITION_FUNCTION), colour="black") +
  geom_bar(aes(colour =POSITION_FUNCTION), stat="identity", position = "fill" ) +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10,face="bold")
labs(title="POSITION_FUNCTION across top 3 city in 3 countries" , x="", y="Number of people coming in state | number |
```

## POSITION\_FUNCTION across top 3 city in 3 countries



```
# cramer v    POSITION_FUNCTION X CITY OF DESTINATION (top 3)
x<- top3cit$DESTINATION_REGION
y<- top3cit$POSITION_FUNCTION

cv.test = function(x,y) {
    CV = sqrt(chisq.test(x, y, correct=FALSE)$statistic /
        (length(x) * (min(length(unique(x)),length(unique(y))) - 1)))</pre>
```

```
print.noquote("Cramér V / Phi:")
  return(as.numeric(CV))
with(top3cit, cv.test(x, y)) # [1] Cramér V / Phi: [1] 0.1318759
## Warning in chisq.test(x, y, correct = FALSE): Chi-squared approximation may be
## incorrect
## [1] Cramér V / Phi:
## [1] 0.1318759
# how about across all cities? (lower)
x<- both DESTINATION REGION
y<- both POSITION_FUNCTION
cv.test = function(x,y) {
 CV = sqrt(chisq.test(x, y, correct=FALSE)$statistic /
    (length(x) * (min(length(unique(x)),length(unique(y))) - 1)))
 print.noquote("Cramér V / Phi:")
  return(as.numeric(CV))
}
with(both, cv.test(x, y)) # [1] Cramér V / Phi: [1] 0.07209771
## Warning in chisq.test(x, y, correct = FALSE): Chi-squared approximation may be
## incorrect
## [1] Cramér V / Phi:
## [1] 0.07209771
```

## 5. DOMESTIC MIGRATION

comparative analysis of domestic / patterns of internal migration in each country I will focus on the sector per city which seems the most significant bivariate association

```
# select only USA
both_USA <- both %>% filter(SOURCE_COUNTRY=="United States" & DESTINATION_COUNTRY=="United States")
# select only Australia
both_AUS <- both %>% filter(SOURCE_COUNTRY=="Australia" & DESTINATION_COUNTRY=="Australia")
# select only UK
both_UK <- both %>% filter(SOURCE_COUNTRY=="United Kingdom" & DESTINATION_COUNTRY=="United Kingdom")
```

construct different samples

```
both_USA_N <- both_USA %>% group_by(DESTINATION_REGION) %>% summarise(numIMM = n())
both_USA_N
```

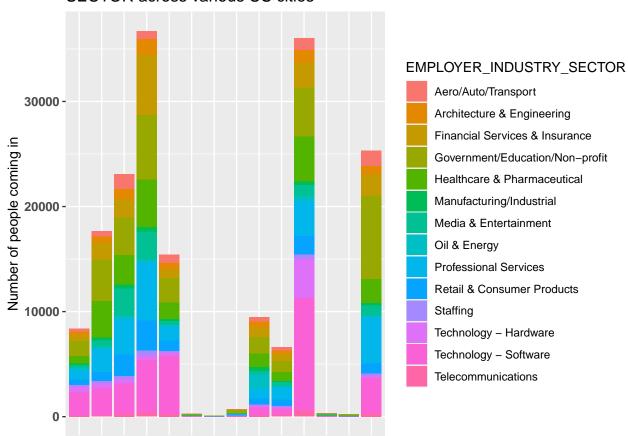
construct USA internal sub-sample (for simplicity)

```
## # A tibble: 212 x 2
##
     DESTINATION_REGION
                                     numIMM
      <fct>
                                      <int>
##
  1 Abilene, Texas Area
##
                                         59
   2 Albany, New York Area
                                       1165
  3 Albuquerque, New Mexico Area
                                        335
  4 Allentown, Pennsylvania Area
                                        728
## 5 Anchorage, Alaska Area
                                         79
   6 Asheville, North Carolina Area
                                        205
## 7 Athens, Georgia Area
                                        311
## 8 Auburn, Alabama Area
                                         60
## 9 Augusta, Georgia Area
                                        201
## 10 Austin, Texas Area
                                       8401
## # i 202 more rows
some_USA <- both_USA [both_USA DESTINATION_REGION == "Greater New York City Area" | both_USA DESTINATION
                    | both_USA$DESTINATION_REGION == "Green Bay, Wisconsin Area" | both_USA$DESTINATION
summary(some_USA)
                     HIGHEST DEGREE OBTAINED
##
      NEW MEM ID
                                                SENIORITY
##
   Min. :
                     associate:25165
                                             Entry
                                                     :84953
   1st Qu.:112192
                     bachelor:94375
                                             Senior :55988
  Median :228366
                     doctor :18926
                                             Manager: 15747
                                             Training: 8991
## Mean
         :231103
                     master
                              :41950
                                             Director: 7716
##
   3rd Qu.:348236
##
  Max. :475316
                                                    : 2776
##
                                             (Other): 4245
                                                           POSITION_FUNCTION
##
                       EMPLOYER_INDUSTRY_SECTOR
## Technology - Software
                                   :33788
                                                                    :26427
                                                Engineering
## Government/Education/Non-profit:33090
                                                Education
                                                                    :15830
## Professional Services
                                   :23385
                                                Research
                                                                    :15050
## Healthcare & Pharmaceutical
                                                Sales
                                   :22185
                                                                    :12712
## Financial Services & Insurance :16524
                                                Business Development: 11655
## Retail & Consumer Products
                                                Operations
                                   :11439
                                                                    :11573
   (Other)
##
                                   :40005
                                                (Other)
                                                                    :87169
                              SOURCE_COUNTRY
      WEEK_BEGINNING
                                                                  SOURCE_REGION
##
##
  7/31/2016: 4510
                       Australia
                                               Greater New York City Area: 15572
                                    :
  8/14/2016: 4505
                      United Kingdom:
                                               San Francisco Bay Area
## 8/21/2016: 4493
                      United States: 180416
                                               Greater Los Angeles Area :
                                                                           9648
                                               Greater Boston Area
## 8/28/2016: 4354
                                                                            8611
                                               Washington D.C. Metro Area:
## 9/11/2016: 4327
##
  6/5/2016 : 4289
                                               Greater Chicago Area
                                                                            6984
##
    (Other) :153938
                                               (Other)
                                                                         :122226
##
       DESTINATION COUNTRY
                                             DESTINATION REGION
##
  Australia
                            Greater New York City Area: 36695
                            San Francisco Bay Area
  United Kingdom:
                            Washington D.C. Metro Area: 25335
  United States: 180416
##
                            Greater Los Angeles Area :23073
##
                            Greater Boston Area
                            Greater Seattle Area
##
                                                      :15436
##
                            (Other)
                                                      :26147
```

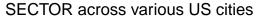
#### 5.1 Bivariate measures of assiciation USA - sector

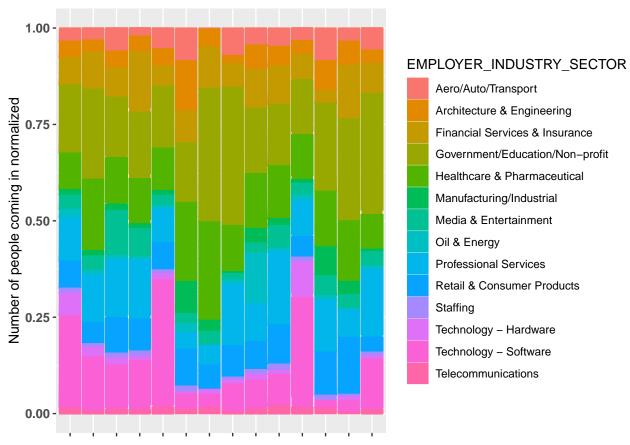
```
# qplot for visualization
qplot(x = DESTINATION_REGION, data = some_USA, fill = EMPLOYER_INDUSTRY_SECTOR, geom = "bar") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10,face="bold")
labs(title="SECTOR across various US cities", x="", y="Number of people coming in")
```

#### SECTOR across various US cities











```
# cramer v Sector X CITY OF DESTINATION (top 3)
x<- some_USA$DESTINATION_REGION
y<- some_USA$EMPLOYER_INDUSTRY_SECTOR

cv.test = function(x,y) {
   CV = sqrt(chisq.test(x, y, correct=FALSE)$statistic /
        (length(x) * (min(length(unique(x)),length(unique(y))) - 1)))
   print.noquote("Cramér V / Phi:")
   return(as.numeric(CV))
}</pre>
```

```
with(some_USA, cv.test(x, y)) # [1] Cramér V / Phi: 0.127 (less )

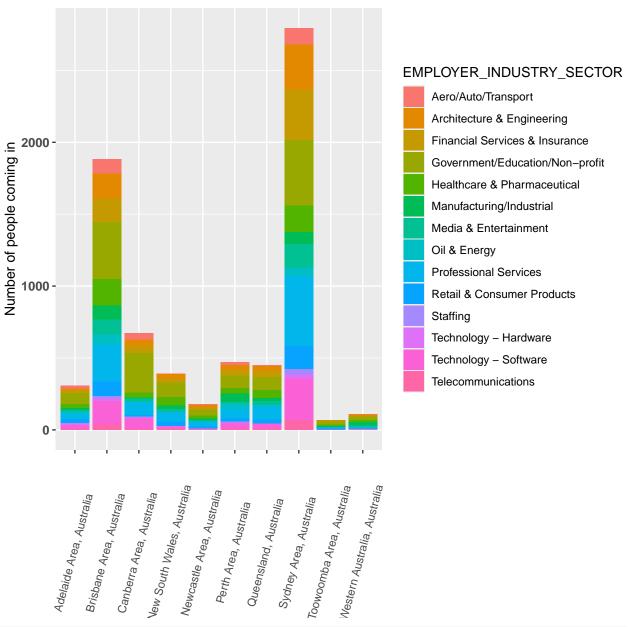
## Warning in chisq.test(x, y, correct = FALSE): Chi-squared approximation may be
## incorrect

## [1] Cramér V / Phi:
## [1] 0.1270301
```

#### 5.2 Bivariate measures of association AUSTRALIA - sector

```
# qplot for visualization
qplot(x = DESTINATION_REGION, data = both_AUS, fill = EMPLOYER_INDUSTRY_SECTOR, geom = "bar") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10,face="bold")
labs(title="SECTOR across AUS cities", x="", y="Number of people coming in")
```

### **SECTOR** across AUS cities



# **SECTOR** across AUS cities 1.00 EMPLOYER\_INDUSTRY\_SECTOR Aero/Auto/Transport Number of people coming in normalized Architecture & Engineering 0.75 Financial Services & Insurance Government/Education/Non-profit Healthcare & Pharmaceutical Manufacturing/Industrial 0.50 -Media & Entertainment Oil & Energy **Professional Services** Retail & Consumer Products Staffing 0.25 Technology - Hardware Technology - Software Telecommunications 0.00 Adelaide Afea, Australia Brisbane Afea, Australia Canberra Afea, Australia Vew South Wales, Australia Newcastle Afea, Australia Perth Afea, Australia

## Warning in chisq.test(x, y, correct = FALSE): Chi-squared approximation may be

```
## incorrect
## [1] Cramér V / Phi:
## [1] 0.1074171
5.3 Bivariate measures of association UK - sector
both_UK_N <- both_UK %>% group_by(DESTINATION_REGION) %>% summarise(numIMM = n())
both_UK_N
construct UK internal sub-sample (for simplicity)
## # A tibble: 60 x 2
##
     DESTINATION_REGION
                                  numIMM
##
      <fct>
                                   <int>
##
   1 Bath, United Kingdom
                                     160
##
   2 Belfast, United Kingdom
                                      66
  3 Birmingham, United Kingdom
                                     949
## 4 Bournemouth, United Kingdom
                                      76
   5 Brighton, United Kingdom
                                     245
## 6 Bristol, United Kingdom
                                     754
## 7 Bromley, United Kingdom
                                     138
## 8 Cambridge, United Kingdom
                                     719
## 9 Canterbury, United Kingdom
                                      55
## 10 Cardiff, United Kingdom
                                     226
## # i 50 more rows
some_UK <- both_UK[both_UK$DESTINATION_REGION == "London, United Kingdom" | both_UK$DESTINATION_REGION
                    | both_UK$DESTINATION_REGION == "Bromley, United Kingdom" | both_UK$DESTINATION_REG
                    , ]
summary(some_UK)
##
      NEW_MEM_ID
                     HIGHEST_DEGREE_OBTAINED
                                                SENIORITY
##
   Min.
                18
                     associate: 677
                                             Entry
                                                     :8439
          :
   1st Qu.:163777
                     bachelor:13336
                                             Senior:8351
  Median :286759
                              : 2093
                                             Manager: 2520
##
                     doctor
##
   Mean
           :271096
                     master
                              : 5773
                                             Training: 1057
##
   3rd Qu.:385509
                                             Director: 754
##
  Max.
           :475315
                                                     : 254
##
                                              (Other):504
##
                       EMPLOYER_INDUSTRY_SECTOR
                                                           POSITION_FUNCTION
## Professional Services
                                                Business Development: 1927
                                   :4481
## Financial Services & Insurance :3093
                                                Sales
                                                                     : 1773
## Government/Education/Non-profit:2757
                                                Engineering
                                                                     : 1572
## Technology - Software
                                                Finance
                                   : 2586
                                                                     : 1539
## Media & Entertainment
                                   :1819
                                                Operations
                                                                     : 1464
## Retail & Consumer Products
                                   :1598
                                                Research
                                                                     : 1462
##
   (Other)
                                   :5545
                                                 (Other)
                                                                     :12142
##
      WEEK_BEGINNING
                             SOURCE_COUNTRY
## 10/2/2016: 673
                      Australia
                                    :
```

United Kingdom: 21879

United States:

## 9/18/2016: 616

## 9/4/2016 : 575

603

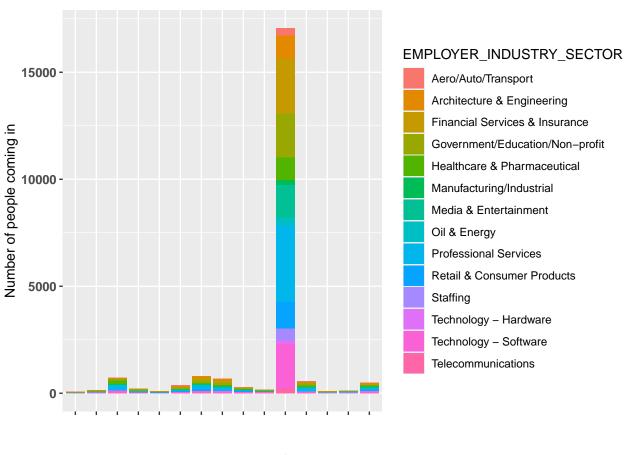
583

## 9/11/2016:

## 9/25/2016:

```
## 10/9/2016: 565
## (Other) :18264
                                SOURCE REGION
                                                   DESTINATION COUNTRY
##
## London, United Kingdom
                                      : 2192
                                               Australia
                                                          :
## Manchester, United Kingdom
                                               United Kingdom:21879
                                       : 816
## Oxford, United Kingdom
                                         767
                                               United States :
## Reading, United Kingdom
                                       : 719
## Twickenham, United Kingdom
                                       : 712
## Kingston upon Thames, United Kingdom: 699
                                       :15974
## (Other)
                    DESTINATION_REGION
##
## London, United Kingdom
                             :17055
## Edinburgh, United Kingdom: 803
## Cambridge, United Kingdom:
                                719
## Glasgow, United Kingdom
                                682
## Oxford, United Kingdom
                                554
## Twickenham, United Kingdom: 492
## (Other)
                             : 1574
# qplot for visualization
qplot(x = DESTINATION_REGION, data = some_UK, fill = EMPLOYER_INDUSTRY_SECTOR, geom = "bar") +
theme(axis.text.x = element_text(angle=75, vjust=0.3), axis.text.y = element_text(size=10, face="bold")
labs(title="SECTOR across some UK cities", x="", y="Number of people coming in")
```

#### SECTOR across some UK cities





# SECTOR across some UK cities 1.00 EMPLOYER\_INDUSTRY\_SECTOR Aero/Auto/Transport Number of people coming in normalized Architecture & Engineering 0.75 Financial Services & Insurance Government/Education/Non-profit Healthcare & Pharmaceutical Manufacturing/Industrial 0.50 -Media & Entertainment Oil & Energy **Professional Services** Retail & Consumer Products Staffing 0.25 -Technology - Hardware Technology - Software **Telecommunications**



0.00

## Warning in chisq.test(x, y, correct = FALSE): Chi-squared approximation may be

- ## incorrect
- ## [1] Cramér V / Phi:
- ## [1] 0.07060599