

Nationality-Based Discrimination in Mexico's Refugee Determination Process

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Introduction

The 1951 United Nations Refugees Convention establishes the fundamental framework of international asylum law for member states of the United Nations. Since 1951, member states have met in other conventions to re-contextualize and re-interpret this legal framework in new correspondence to their national interests and needs (OAU Convention 1969 & 1984 Cartagena Declaration), but the legal principles establishing the definition of a refugee remain identical since its conception. According to the 1951 Convention, a refugee is any person that based on a well-founded fear of persecution on the basis of their race, religion, nationality, membership to a particular social group, or political opinion, merits the international protection of a sovereign entity outside of their country of origin. As it stands, in 2022, approximately 108.4 million people were forcibly displaced, and of those forcibly displaced, 35.3 million were categorized as refugees. According to the UNHCR, 76% of the world's refugees are hosted in low and middle-income countries across the world.

Since its inception, Mexico has not historically been a destination country for migrants and refugees. At most, the country became a transit country for Central and South American migrants that headed to the United States during periods of increased generalized drug violence, civil wars, and economic destitution between the late 1980s and early 2000s. Over the last decade alone, the number of refugee applications submitted to and processed by the Mexican government has exponentially increased, and this data is indicative of Mexico's evolving role as a destination country for many immigrants. However, given the exponential increase in applications and Mexico's limited institutional capacity as a middle-income country, questions have emerged whether COMAR, Mexico's refugee processing institution, selective prioritizes applications of certain nationalities and therefore discriminates against others. I would like to explore this phenomenon, and compile/analyze data that uncover potential discriminatory institutional practices on the basis of Hispanic and non-Hispanic categorizations, as well as suggest potential policy recommendations. I am planning to use data from the Mexican Commission for Refugee Assistance.

Project Abstract

Does a migrant's nationality impact the probability that they get refugee status granted in Mexico? In my research project, I hypothesize, that migrants who indicate a Hispanic nationality tend to have higher possibilities to successfully obtain refugee status in Mexico. As a result, I expect that migrants from Haiti, the non-Spanish Caribbean, and other parts of the world tend to have lower possibilities at refugee resettlement. Additionally, though the Mexican Government has made advances to expand their refugee granting criteria, because the 1951 UN Convention of Refugees provides a large number of successful refugee claims to migrants with "well-founded fear of persecution", then I also predict that Mexican institutions accept Spanish-speaking Latin-Americans at a significant larger rate. For this project, I will analyze the Mexican Government's Commission on Refugee Assistance open data set that I will use to assess the several reasons that migrants tend to leave their countries of origin. My unit of measurement is whether an immigrant was granted refugee status or not. If the immigrant was provided with a refugee status, implying that the migrant was considered to have had a well-founded fear of persecution, then I will indicate that with 1 for successful application. If a migrant was rejected, then I will indicate that with 0. The independent variable will be the migrant's nationality. The explanatory variable of interest is whether the nationality impacts

the likelihood that a migrant gets refugee status in Mexico. If Venezuelans, Hondurans, and other spanish speaking Latin Americans have a higher rate of refugee success, then that will make my hypothesis correct. If other types of nationalities have a higher rate of success, then I will be proven wrong. In any case, I am also interested in observing the variability of application success and the type of application submitted.

```
#set up all libraries needed for this project
```

```
library(tidyverse, ggplot2)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
```

```
## v dplyr      1.1.3      v readr      2.1.4
```

```
## v forcats    1.0.0      v stringr    1.5.0
```

```
## v ggplot2    3.4.3      v tibble     3.2.1
```

```
## v lubridate  1.9.2      v tidyr      1.3.0
```

```
## v purrr      1.0.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
```

```
## x dplyr::lag()     masks stats::lag()
```

```
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
#import data needed
```

```
submitted_applications <- read.csv("//Users//jvenancio//Downloads//COMAR_Thesis_Data_Solicitudes.csv")
```

```
application_results <- read.csv("//Users//jvenancio//Downloads//COMAR_Thesis_Data_Resoluciones.csv")
```

```
#count how many applications were submitted per nationality + create data table
```

```
apps_sub_per_nationality <- submitted_applications |>
```

```
  count(NACIONALIDAD) |>
```

```
  rename(applications = n, Nationality = NACIONALIDAD)
```

```
#count how many applications were submitted per year + create data table
```

```
apps_sub_per_year <- submitted_applications |>
```

```
  count(AÑO) |>
```

```
  rename(applications = n, year = AÑO)
```

```
# Assuming 'submitted_applications' is your data frame
```

```
#count how many applications were processed per year + create data table
```

```
apps_proc_per_year <- application_results |>
```

```
  count(AÑO_RESOLUCION) |>
```

```
  rename(applications = n, year = AÑO_RESOLUCION)
```

```
#count the end result of the applications that were processed in total from 2013-23
```

```
apps_proc_result <- application_results |>
```

```
  count(SENTIDO_RESOLUCIÓN)
```

```
# Print the data table
```

```
print(apps_sub_per_year)
```

```
##      year applications
```

```
## 1  2013           911
```

```
## 2  2014          1370
```

```
## 3  2015          2105
```

```
## 4  2016          5002
```

```
## 5 2017          9594
## 6 2018         18325
## 7 2019         41063
## 8 2020         27977
## 9 2021         74489
## 10 2022        82326
## 11 2023        68205
```

```
#count the end result of the applications that were processed (positive) in total from 2013-23 per nati
apps_proc_result_pos <- application_results |>
  filter(SENTIDO_RESOLUCIÓN == "Resolución Positiva")

table(apps_proc_result_pos$NACIONALIDAD)
```

```
##
##              Afganistán              Angola
##                6                6
##              Argelia              Argentina
##                1                6
##            Bangladesh              Belice
##                7                4
##              Benín              Brasil
##                6                4
##            Burkina Faso              Camerún
##               14               44
##                Chad              Chile
##                1                6
##              China              Colombia
##                1              257
##              Congo              Costa de Marfil
##               16                2
##            Costa Rica              Cuba
##                5             4001
##            Ecuador              Egipto
##               59                4
##            El Salvador              EL SALVADOR
##            8470                19
##            Eritrea              España
##                1                3
##      Estados Unidos de América              Etiopía
##                1                2
##      Federación de Rusia              Georgia
##               48                1
##              Ghana              Granada
##               38                1
##            Guatemala              GUATEMALA
##            2211                10
##              Guinea              Guinea Ecuatorial
##               38                1
##      Guinea-Bissau              Haití
##                1             2190
##              Honduras              Hong Kong
##            27115                1
##              Hungría              India
```

##	1	4
##	Irak	Irán
##	12	10
##	Israel	Jamaica
##	2	7
##	Kirguistán	Mali
##	1	2
##	Marruecos	Mauritania
##	5	6
##	Nepal	Nicaragua
##	1	1291
##	NICARAGUA	Nígeria
##	3	34
##	Países Bajos	Pakistán
##	1	8
##	Palestina	Panamá
##	5	3
##	Perú	República de Kazajstán
##	14	1
##	Republica de Turquía	República Democrática del Congo
##	5	13
##	República Dominicana	República Islámica de Irán
##	25	1
##	Rusia	Rwanda
##	4	1
##	Senegal	Sierra Leona
##	3	9
##	Siria	Somalia
##	32	2
##	Sri Lanka	Tanzania
##	3	1
##	Tayikistán	Togo
##	1	18
##	Ucrania	Uganda
##	49	2
##	Uruguay	Uzbekistán
##	4	1
##	Venezuela	VENEZUELA
##	16366	198
##	Yemen	
##	29	

```
apps_proc_result_neg <- application_results |>
  filter(SENTIDO_RESOLUCIÓN == "Resolución Negativa")

table(apps_proc_result_neg$NACIONALIDAD)
```

##		
##	Afganistán	Albania
##	1	4
##	Alemania	Angola
##	5	5
##	Argentina	Austria
##	120	1

##	Bangladesh	Bélgica
##	2	1
##	Belice	Benín
##	8	2
##	Bolivia	Brasil
##	10	27
##	Burkina Faso	Camerún
##	15	24
##	Canadá	Chile
##	2	22
##	China, República Popular	Colombia
##	14	1013
##	Congo	Corea del Sur
##	7	1
##	Costa de Marfil	Costa Rica
##	9	22
##	Cuba	CUBA
##	4614	7
##	Dominica	Ecuador
##	2	88
##	El Salvador	EL SALVADOR
##	3431	35
##	España	Estados Unidos de América
##	14	23
##	Etiopia	Federación de Rusia
##	1	42
##	Francia	Gambia
##	3	2
##	Ghana	Guatemala
##	64	2242
##	GUATEMALA	Guinea
##	9	8
##	Guinea Ecuatorial	Guinea-Bissau
##	1	1
##	Guyana	Haití
##	2	10486
##	Haití	Honduras
##	3	8111
##	Hungría	India
##	2	33
##	Irak	Irán
##	1	1
##	Israel	Italia
##	2	6
##	Jamaica	Japón
##	4	1
##	Líbano	Libia
##	2	1
##	Macedonia	Mali
##	1	6
##	Marruecos	Mauritania
##	1	2
##	Nicaragua	NICARAGUA
##	1324	8

##	Nigeria	Nigeria
##	2	41
##	Países Bajos (Holanda)	Pakistán
##	1	8
##	Panamá	Paraguay
##	11	2
##	Perú	Polonia
##	70	3
##	Portugal	Reino Unido
##	6	1
##	República Checa	República de Guinea-Bissau
##	1	1
##	República de Suriname	Republica de Turquía
##	2	4
##	República Democrática del Congo	República Dominicana
##	4	83
##	Rumania	Rusia
##	2	2
##	Senegal	Sierra Leona
##	5	6
##	Singapur	Somalia
##	1	8
##	Sri Lanka	Suiza
##	1	1
##	Tailandia	Togo
##	1	8
##	Trinidad y Tobago	Ucrania
##	1	5
##	Uruguay	Venezuela
##	9	880
##	VENEZUELA	
##	2	

Paragraph Summary:

These two data pieces are essential to answer my research question. As a reminder, I am investigating whether the nationality of an applicant impacts the likelihood that they receive refugee status in Mexico. My hypothesis was that if an applicant is from a Spanish-speaking country, then they are more likely to acquire refugee status. If an applicant is from a non-Spanish-speaking country, then they are more likely to get rejected.

Based on these data visuals, my hypothesis is correct. First, the nationality that is the most impacted is Haiti. According to my data set, while 2190 Haitians managed to acquire refugee status in Mexico, 10486 Haitian applicants have been rejected over the last decade. Haiti is a country in the Caribbean, whose official language is Haitian Creole.

On the contrary, migrants from Venezuela have been overwhelmingly granted refugee status over the last decade. Only 882 Venezuelans were denied refugee status, and 16,366 Venezuelans were granted refugee status. Venezuela is a Spanish-speaking country in South-America.

The reason why I specifically analyzed both cases is because arguably the biggest differences in their country's context are ethnic and cultural backgrounds. Both countries are experiencing the largest political instability contexts in contemporary Latin-American history, and are often impacted by economic and environmental destitution in the same. I would have expected that if nationality and the corresponding racial implications were not contributing determinants to refugee acquisition, then applicants from these two countries would

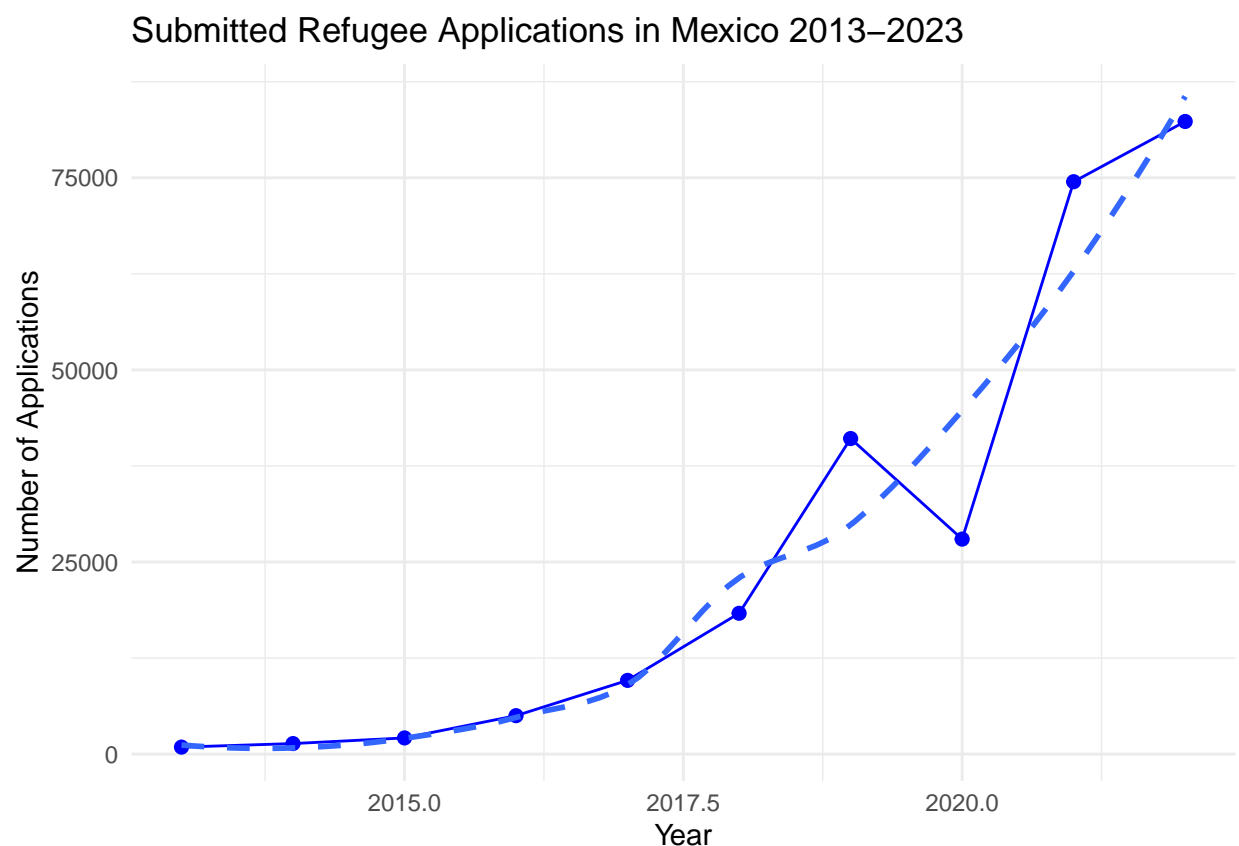
have been admitted at statistically similar rates. However, despite their similar political and economic contexts, there is a drastically different outcome in refugee status determination in Mexico.

```
library(ggplot2)

# data frames: apps_sub_per_year, apps_proc_per_year, apps_proc_result

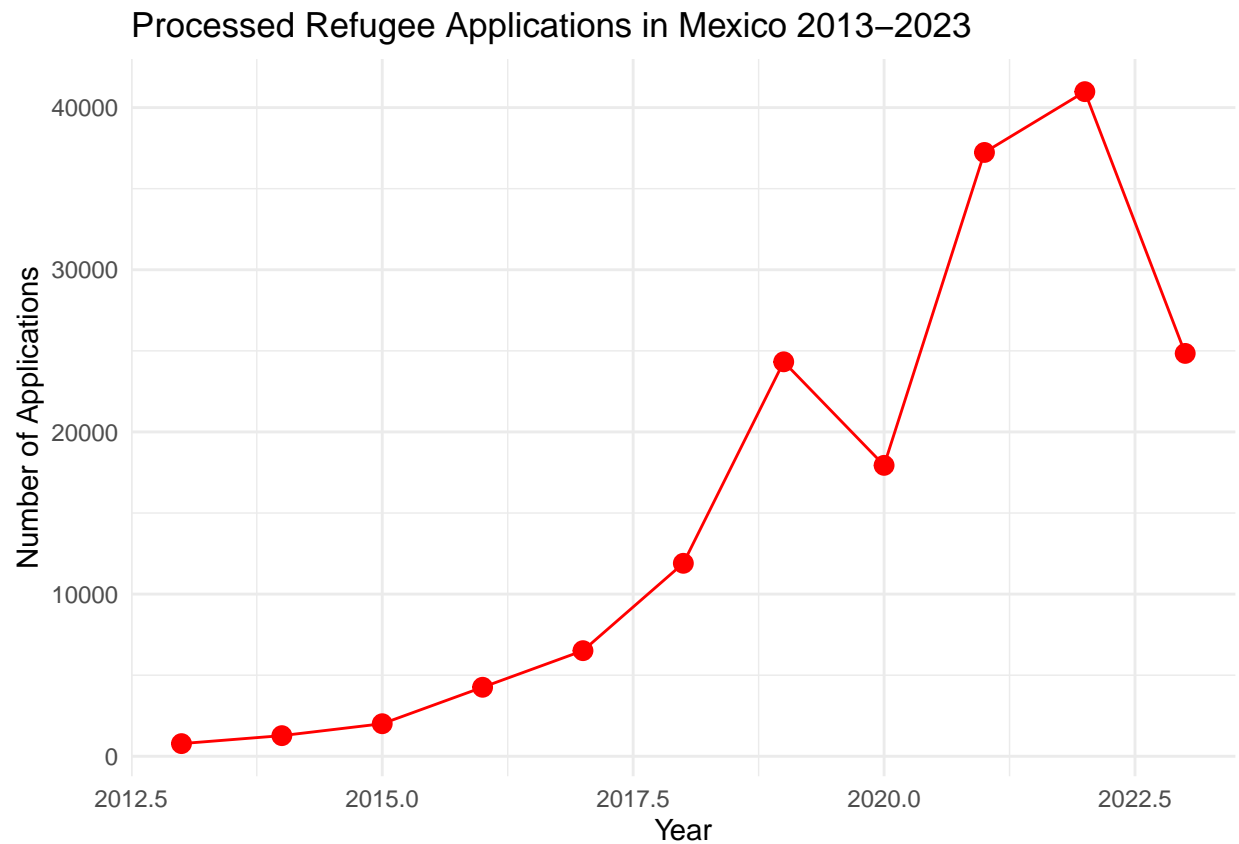
# Creating the line graph for submitted applications per year
ggplot(data = apps_sub_per_year %>% filter(year != 2023),
       aes(x = year, y = applications, group = 1)) +
  geom_line(color = "blue") +
  geom_point(color = "blue", size = 2) +
  geom_smooth(linetype = 2, se = FALSE) +
  labs(title = "Submitted Refugee Applications in Mexico 2013-2023",
       x = "Year",
       y = "Number of Applications") +
  theme_minimal()
```

```
## 'geom_smooth()' using method = 'loess' and formula = 'y ~ x'
```



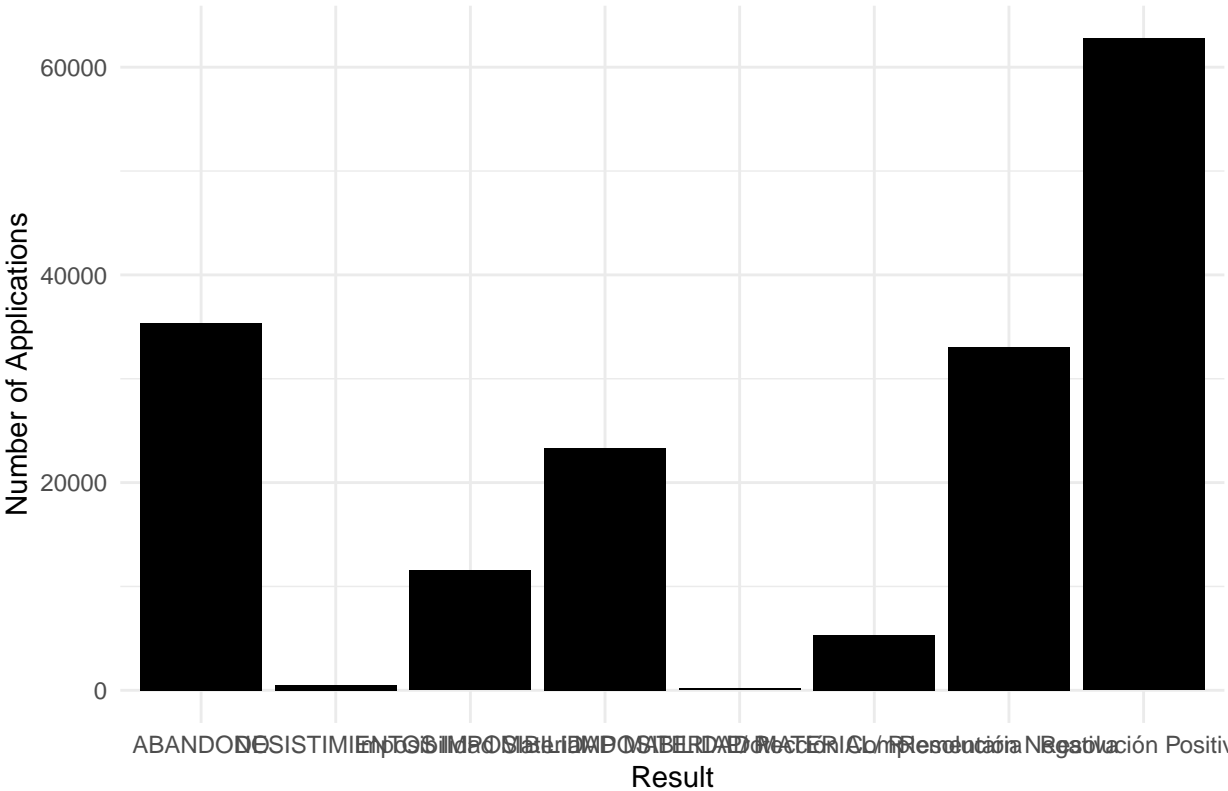
```
# Creating the line graph for processed applications per year
ggplot(data = apps_proc_per_year, aes(x = year, y = applications, group = 1)) +
  geom_line(color = "red") +
  geom_point(color = "red", size = 3) +
  labs(title = "Processed Refugee Applications in Mexico 2013-2023",
```

```
x = "Year",
y = "Number of Applications") +
theme_minimal()
```



```
# Creating a bar plot for the result of processed applications
ggplot(data = apps_proc_result, aes(x = SENTIDO_RESOLUCIÓN, y = n)) +
  geom_bar(stat = "identity", fill = "black") +
  labs(title = "Result of Processed Asylum Applications in Mexico 2013-2023",
        x = "Result",
        y = "Number of Applications") +
  theme_minimal()
```

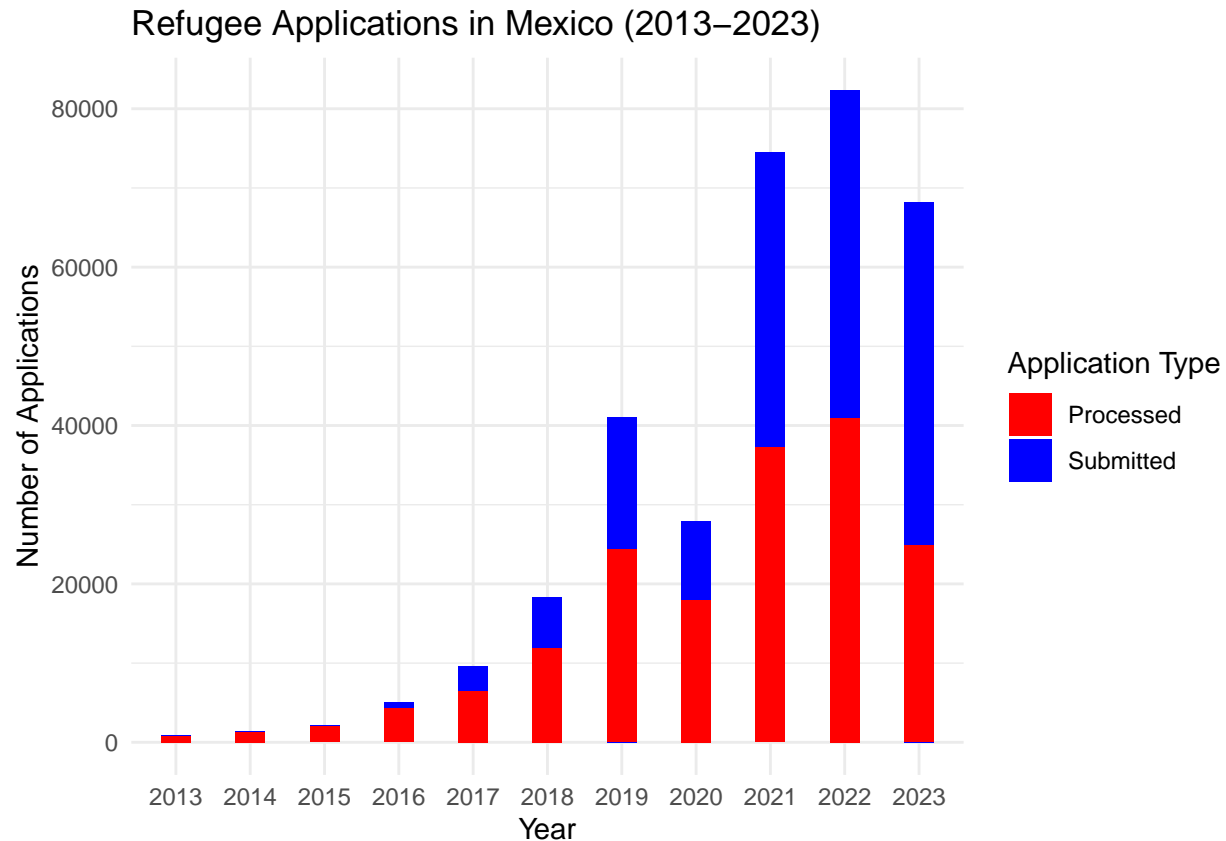

Result of Processed Asylum Applications in Mexico 2013–2023



```
library(ggplot2)
```

```
merged_data <- merge(apps_sub_per_year, apps_proc_per_year, by = "year", all = TRUE)
```

```
ggplot(data = merged_data, aes(x = as.factor(year))) +
  geom_bar(aes(y = applications.x, fill = "Submitted"), stat = "identity", position = "dodge", width = 0.8) +
  geom_bar(aes(y = applications.y, fill = "Processed"), stat = "identity", position = "dodge", width = 0.8) +
  labs(title = "Refugee Applications in Mexico (2013-2023)",
       x = "Year",
       y = "Number of Applications") +
  scale_fill_manual(name = "Application Type", values = c("Submitted" = "blue", "Processed" = "red")) +
  theme_minimal()
```



Paragraph: Since 2013, the number of refugee applications in Mexico have exponentially increased. Simultaneously, this bar graph indicates how Mexico has also processed, though not completely, refugee applications over the years. This graph indicates that Mexico has become a destination country, and every year there is an increasing number of migrants that attempt to permanently resettle in the country.

```
library(dplyr)

spanish_speaking_countries <- c("Argentina", "Chile", "Colombia", "Costa Rica", "Cuba", "Ecuador", "El Salvador", "Guatemala", "Honduras", "Nicaragua", "Panama", "Paraguay", "Peru", "Puerto Rico", "Uruguay", "Venezuela")

data <- application_results |>
  mutate(spanish_speaking = if_else(NACIONALIDAD %in% spanish_speaking_countries, 1, 0),
         approved = if_else(SENTIDO_RESOLUCIÓN == "Resolución Positiva", 1, 0))

fit1 <- lm(approved ~ spanish_speaking, data = data)

summary(fit1)

##
## Call:
## lm(formula = approved ~ spanish_speaking, data = data)
##
## Residuals:
```

```
##      Min      1Q   Median      3Q      Max
## -0.42004 -0.42004 -0.09336  0.57996  0.90664
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.093359   0.002732   34.18  <2e-16 ***
## spanish_speaking 0.326678   0.002996  109.03  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4656 on 172051 degrees of freedom
## Multiple R-squared:  0.06462,    Adjusted R-squared:  0.06462
## F-statistic: 1.189e+04 on 1 and 172051 DF,  p-value: < 2.2e-16
```

```
# Install and load necessary packages if not already installed
if (!requireNamespace("ggplot2", quietly = TRUE)) {
  install.packages("ggplot2")
}
if (!requireNamespace("dplyr", quietly = TRUE)) {
  install.packages("dplyr")
}

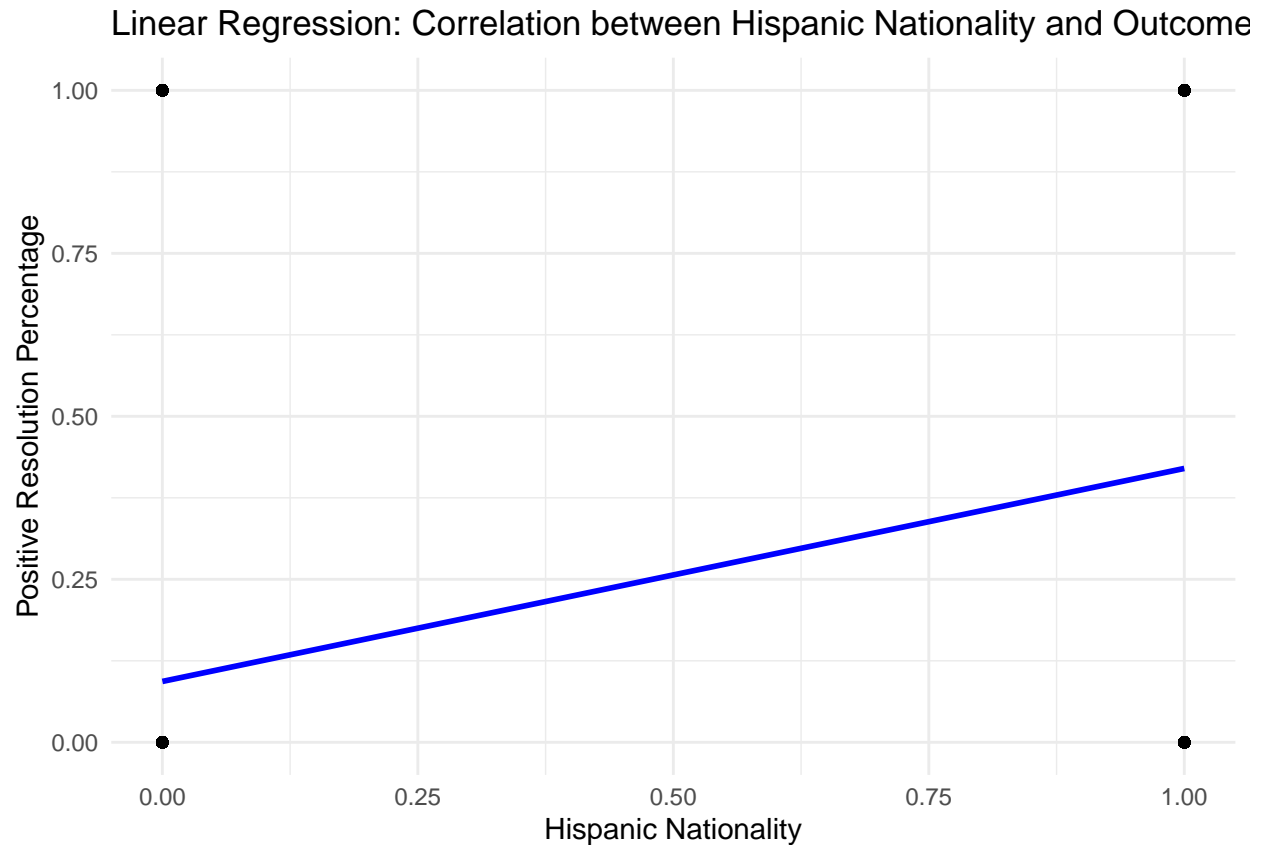
# Load libraries
library(ggplot2)
library(dplyr)

# Your linear regression model
model <- lm(formula = approved ~ spanish_speaking, data = data)

# Create a dataframe for predictions
predictions <- data.frame(data, predicted = predict(model))

# Plotting the data and the regression line
ggplot(predictions, aes(x = spanish_speaking, y = approved)) +
  geom_point() + # Scatter plot of the data points
  geom_line(aes(x = spanish_speaking, y = predicted), color = "blue", size = 1) + # Regression line
  labs(title = "Linear Regression: Correlation between Hispanic Nationality and Outcome",
        x = "Hispanic Nationality",
        y = "Positive Resolution Percentage") +
  theme_minimal()
```

```
## 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.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.
```



```
# Assuming 'application_results' is your data frame
library(dplyr)
library(knitr)

# Filter for positive resolutions
apps_proc_result_pos <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Positiva")

# Count applications per nationality for positive resolutions
table_result <- table(apps_proc_result_pos$NACIONALIDAD)

# Create a nice table
kable(data.frame(Nationality = names(table_result), Applications = as.vector(table_result)),
      col.names = c("Nationality", "Applications"),
      caption = "Number of Applications with Positive Resolutions Per Nationality")
```

Table 1: Number of Applications with Positive Resolutions Per Nationality

Nationality	Applications
Afganistán	6
Angola	6
Argelia	1
Argentina	6

Nationality	Applications
Bangladesh	7
Belice	4
Benín	6
Brasil	4
Burkina Faso	14
Camerún	44
Chad	1
Chile	6
China	1
Colombia	257
Congo	16
Costa de Marfil	2
Costa Rica	5
Cuba	4001
Ecuador	59
Egipto	4
El Salvador	8470
EL SALVADOR	19
Eritrea	1
España	3
Estados Unidos de América	1
Etiopia	2
Federación de Rusia	48
Georgia	1
Ghana	38
Granada	1
Guatemala	2211
GUATEMALA	10
Guinea	38
Guinea Ecuatorial	1
Guinea-Bissau	1
Haití	2190
Honduras	27115
Hong Kong	1
Hungría	1
India	4
Irak	12
Irán	10
Israel	2
Jamaica	7
Kirguistán	1
Mali	2
Marruecos	5
Mauritania	6
Nepal	1
Nicaragua	1291
NICARAGUA	3
Nígeria	34
Países Bajos	1
Pakistán	8
Palestina	5
Panamá	3

Nationality	Applications
Perú	14
República de Kazajstán	1
Republica de Turquía	5
República Democrática del Congo	13
República Dominicana	25
República Islámica de Irán	1
Rusia	4
Rwanda	1
Senegal	3
Sierra Leona	9
Siria	32
Somalia	2
Sri Lanka	3
Tanzania	1
Tayikistán	1
Togo	18
Ucrania	49
Uganda	2
Uruguay	4
Uzbekistán	1
Venezuela	16366
VENEZUELA	198
Yemen	29

```

# Assuming 'application_results' is your data frame
library(dplyr)

# Count applications per positive resolution type
apps_proc_result_pos <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Positiva") %>%
  count(NACIONALIDAD)

# Count applications per negative resolution type
apps_proc_result_neg <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Negativa") %>%
  count(NACIONALIDAD)

# Merge the two tables
merged_table <- merge(apps_proc_result_pos, apps_proc_result_neg, by = "NACIONALIDAD", all = TRUE)

# Rename columns for clarity
colnames(merged_table) <- c("Nationality", "Positive_Resolutions", "Negative_Resolutions")

# Print the merged table
print(merged_table)

```

```

##           Nationality Positive_Resolutions Negative_Resolutions
## 1           Afganistán                6                1
## 2             Albania                NA                4
## 3           Alemania                NA                5
## 4             Angola                6                5

```

## 5	Argelia	1	NA
## 6	Argentina	6	120
## 7	Austria	NA	1
## 8	Bangladesh	7	2
## 9	Bélgica	NA	1
## 10	Belice	4	8
## 11	Benín	6	2
## 12	Bolivia	NA	10
## 13	Brasil	4	27
## 14	Burkina Faso	14	15
## 15	Camerún	44	24
## 16	Canadá	NA	2
## 17	Chad	1	NA
## 18	Chile	6	22
## 19	China	1	NA
## 20	China, República Popular	NA	14
## 21	Colombia	257	1013
## 22	Congo	16	7
## 23	Corea del Sur	NA	1
## 24	Costa de Marfil	2	9
## 25	Costa Rica	5	22
## 26	Cuba	4001	4614
## 27	CUBA	NA	7
## 28	Dominica	NA	2
## 29	Ecuador	59	88
## 30	Egipto	4	NA
## 31	El Salvador	8470	3431
## 32	EL SALVADOR	19	35
## 33	Eritrea	1	NA
## 34	España	3	14
## 35	Estados Unidos de América	1	23
## 36	Etiopia	2	1
## 37	Federación de Rusia	48	42
## 38	Francia	NA	3
## 39	Gambia	NA	2
## 40	Georgia	1	NA
## 41	Ghana	38	64
## 42	Granada	1	NA
## 43	Guatemala	2211	2242
## 44	GUATEMALA	10	9
## 45	Guinea	38	8
## 46	Guinea Ecuatorial	1	1
## 47	Guinea-Bissau	1	1
## 48	Guyana	NA	2
## 49	Haití	2190	10486
## 50	Haití	NA	3
## 51	Honduras	27115	8111
## 52	Hong Kong	1	NA
## 53	Hungría	1	2
## 54	India	4	33
## 55	Irak	12	1
## 56	Irán	10	1
## 57	Israel	2	2
## 58	Italia	NA	6

## 59	Jamaica	7	4
## 60	Japón	NA	1
## 61	Kirguistán	1	NA
## 62	Líbano	NA	2
## 63	Libia	NA	1
## 64	Macedonia	NA	1
## 65	Mali	2	6
## 66	Marruecos	5	1
## 67	Mauritania	6	2
## 68	Nepal	1	NA
## 69	Nicaragua	1291	1324
## 70	NICARAGUA	3	8
## 71	Nigeria	NA	2
## 72	Nígeria	34	41
## 73	Países Bajos	1	NA
## 74	Países Bajos (Holanda)	NA	1
## 75	Pakistán	8	8
## 76	Palestina	5	NA
## 77	Panamá	3	11
## 78	Paraguay	NA	2
## 79	Perú	14	70
## 80	Polonia	NA	3
## 81	Portugal	NA	6
## 82	Reino Unido	NA	1
## 83	República Checa	NA	1
## 84	República de Guinea-Bissau	NA	1
## 85	República de Kazajstán	1	NA
## 86	República de Suriname	NA	2
## 87	Republica de Turquía	5	4
## 88	República Democrática del Congo	13	4
## 89	República Dominicana	25	83
## 90	República Islámica de Irán	1	NA
## 91	Rumania	NA	2
## 92	Rusia	4	2
## 93	Rwanda	1	NA
## 94	Senegal	3	5
## 95	Sierra Leona	9	6
## 96	Singapur	NA	1
## 97	Siria	32	NA
## 98	Somalia	2	8
## 99	Sri Lanka	3	1
## 100	Suiza	NA	1
## 101	Tailandia	NA	1
## 102	Tanzania	1	NA
## 103	Tayikistán	1	NA
## 104	Togo	18	8
## 105	Trinidad y Tobago	NA	1
## 106	Ucrania	49	5
## 107	Uganda	2	NA
## 108	Uruguay	4	9
## 109	Uzbekistán	1	NA
## 110	Venezuela	16366	880
## 111	VENEZUELA	198	2
## 112	Yemen	29	NA


```

# List of countries to filter
selected_countries <- c("Honduras", "El Salvador", "Guatemala", "Haití", "Brasil", "Federación de Rusia")

# Filter the merged table for the selected countries
filtered_merged_table <- merged_table %>%
  filter(Nationality %in% selected_countries)

# Print or further process the filtered merged table
print(filtered_merged_table)

```

##	Nationality	Positive_Resolutions	Negative_Resolutions
## 1	Brasil	4	27
## 2	El Salvador	8470	3431
## 3	Federación de Rusia	48	42
## 4	Ghana	38	64
## 5	Guatemala	2211	2242
## 6	Haití	2190	10486
## 7	Honduras	27115	8111
## 8	India	4	33
## 9	Nicaragua	1291	1324
## 10	Nigeria	34	41
## 11	Venezuela	16366	880

```

# Assuming 'application_results' is your data frame
library(dplyr)

# Count applications per positive resolution type
apps_proc_result_pos <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Positiva") %>%
  count(NACIONALIDAD)

# Count applications per negative resolution type
apps_proc_result_neg <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Negativa") %>%
  count(NACIONALIDAD)

# Merge the two tables
merged_table <- merge(apps_proc_result_pos, apps_proc_result_neg, by = "NACIONALIDAD", all = TRUE)

# Rename columns for clarity
colnames(merged_table) <- c("Nationality", "Positive_Resolutions", "Negative_Resolutions")

# Add a percentage column
merged_table$Percentage_Positive <- paste0(round((merged_table$Positive_Resolutions /
                                                    (merged_table$Positive_Resolutions + merged_table$Negative_Resolutions)) * 100, 2), "%")

# Filter out the total row
filtered_merged_table <- merged_table %>%
  filter(!is.na(Nationality))

# List of countries to filter
selected_countries <- c("Honduras", "El Salvador", "Guatemala", "Haití", "Brasil", "Federación de Rusia")

```

```
# Filter the merged table for the selected countries
filtered_merged_table <- filtered_merged_table %>%
  filter(Nationality %in% selected_countries)

# Print or further process the filtered merged table
print(filtered_merged_table)
```

```
##      Nationality Positive_Resolutions Negative_Resolutions
## 1      Brasil          4                27
## 2    El Salvador      8470             3431
## 3 Federación de Rusia    48              42
## 4      Ghana         38              64
## 5    Guatemala      2211             2242
## 6     Haití         2190            10486
## 7    Honduras     27115             8111
## 8      India         4              33
## 9    Nicaragua     1291             1324
## 10     Nígeria       34              41
## 11    Venezuela    16366             880
##      Percentage_Positive
## 1      12.9%
## 2      71.2%
## 3      53.3%
## 4      37.3%
## 5      49.7%
## 6      17.3%
## 7      77%
## 8      10.8%
## 9      49.4%
## 10     45.3%
## 11     94.9%
```

```
kable(filtered_merged_table, format = "html",
      col.names = c("Nationality", "Positive Resolutions", "Negative Resolutions", "Percentage of Posit
      caption = "Refugee Application Outcomes by Top Hispanic and Non-Hispanic Nationalities")
```

Refugee Application Outcomes by Top Hispanic and Non-Hispanic Nationalities

Nationality

Positive Resolutions

Negative Resolutions

Percentage of Positive Resolutions

Brasil

4

27

12.9%

El Salvador

8470

3431
71.2%
Federación de Rusia
48
42
53.3%
Ghana
38
64
37.3%
Guatemala
2211
2242
49.7%
Haití
2190
10486
17.3%
Honduras
27115
8111
77%
India
4
33
10.8%
Nicaragua
1291
1324
49.4%
Nigeria
34
41
45.3%
Venezuela
16366

880

94.9%

```
# Assuming 'application_results' is your data frame
library(dplyr)
library(knitr)

# Count applications per positive resolution type
apps_proc_result_pos <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Positiva") %>%
  count(NACIONALIDAD)

# Count applications per negative resolution type
apps_proc_result_neg <- application_results %>%
  filter(SENTIDO_RESOLUCIÓN == "Resolución Negativa") %>%
  count(NACIONALIDAD)

# Merge the two tables
merged_table <- merge(apps_proc_result_pos, apps_proc_result_neg, by = "NACIONALIDAD", all = TRUE)

# Rename columns for clarity
colnames(merged_table) <- c("Nationality", "Positive_Resolutions", "Negative_Resolutions")

# Add a percentage column (rounded to the nearest whole number)
merged_table$Percentage_Positive <- paste0(round((merged_table$Positive_Resolutions /
                                                (merged_table$Positive_Resolutions + merged_table$Negative_Resolutions)) * 100), "%")

# Filter out the total row
filtered_merged_table <- merged_table %>%
  filter(!is.na(Nationality))

# List of countries to filter
selected_countries <- c("Honduras", "El Salvador", "Guatemala", "Haití", "Brasil", "Federación de Rusia", "Venezuela")

# Filter the merged table for the selected countries
filtered_merged_table <- filtered_merged_table %>%
  filter(Nationality %in% selected_countries)
filtered_merged_table <- arrange(filtered_merged_table, desc(Percentage_Positive))

# Create a nice-looking table
kable(filtered_merged_table, format = "html",
      col.names = c("Nationality", "Positive Resolutions", "Negative Resolutions", "Percentage of Positive Resolutions"),
      caption = "Refugee Application Outcomes for Top Hispanic and Non-Hispanic Nationalities (2013-2023)")
```

Refugee Application Outcomes for Top Hispanic and Non-Hispanic Nationalities (2013-2023)

Nationality

Positive Resolutions

Negative Resolutions

Percentage of Positive Resolutions

Venezuela

16366

880
95%
Honduras
27115
8111
77%
El Salvador
8470
3431
71%
Federación de Rusia
48
42
53%
Guatemala
2211
2242
50%
Nicaragua
1291
1324
49%
Nigeria
34
41
45%
Ghana
38
64
37%
Haití
2190
10486
17%
Brasil
4

27

13%

India

4

33

11%

```
# Assuming 'filtered_merged_table' is your data frame
library(dplyr)
library(ggplot2)

# Filter the data for Venezuela and Haiti
venezuela_data <- filtered_merged_table %>%
  filter(Nationality == "Venezuela")

haiti_data <- filtered_merged_table %>%
  filter(Nationality == "Haití")

# Check if the filtered data frames are not empty
if (nrow(venezuela_data) > 0 && nrow(haiti_data) > 0) {
  # Combine the data for Venezuela and Haiti
  bar_data <- rbind(venezuela_data, haiti_data)

  # Create a side-by-side bar plot
  ggplot(bar_data, aes(x = Nationality, y = Positive_Resolutions, fill = Nationality)) +
    geom_bar(stat = "identity", position = "dodge") +
    labs(title = "Positive Resolutions of Venezuelan and Haitian Applicants",
         x = "Nationality",
         y = "Count") +
    scale_fill_manual(values = c("Venezuela" = "lightblue", "Haití" = "lightgreen")) +
    theme_minimal()
} else {
  cat("No data found for Venezuela or Haiti.\n")
}
```

Positive Resolutions of Venezuelan and Haitian Applicants

