BIOS512_FinalProject_Williams (1) (4) (1) (1)

November 27, 2025

BIOS512 FINAL PROJECT BELLA WILLIAMS

```
[22]: library(tidyverse)
```

```
[23]: install.packages('fivethirtyeight')
      install.packages('fivethirtyeightdata', repos = 'https://fivethirtyeightdata.
       ↪github.io/drat/', type = 'source')
```

Installing package into '/srv/rlibs'
(as 'lib' is unspecified)

Installing package into '/srv/rlibs'
(as 'lib' is unspecified)

```
[24]: library(fivethirtyeight)
      data("airline_safety")
```

Part I: Preparing the Data

```
[25]: head(airline_safety)
```

A tibble: 6 × 9

airline	incl_reg_subsidiaries	avail_seat_km_per_week	incidents_85_99
\<chr\>	\<lgl\>	\<dbl\>	\<int\>
Aer Lingus	FALSE	320906734	2
Aeroflot	TRUE	1197672318	76
Aerolineas Argentinas	FALSE	385803648	6
Aeromexico	TRUE	596871813	3
Air Canada	FALSE	1865253802	2
Air France	FALSE	3004002661	14

```
[26]: str(airline_safety)

      summary(airline_safety)

      mean(airline_safety$fatalities_85_99)
      mean(airline_safety$fatalities_00_14)
```

1

```
tibble [56 × 9] (S3: tbl_df/tbl/data.frame)
 $ airline              : chr [1:56] "Aer Lingus" "Aeroflot" "Aerolineas
Argentinas" "Aeromexico" …
 $ incl_reg_subsidiaries : logi [1:56] FALSE TRUE FALSE TRUE FALSE FALSE …
 $ avail_seat_km_per_week: num [1:56] 3.21e+08 1.20e+09 3.86e+08 5.97e+08
1.87e+09 …
 $ incidents_85_99      : int [1:56] 2 76 6 3 2 14 2 3 5 7 …
 $ fatal_accidents_85_99 : int [1:56] 0 14 0 1 0 4 1 0 0 2 …
 $ fatalities_85_99     : int [1:56] 0 128 0 64 0 79 329 0 0 50 …
 $ incidents_00_14      : int [1:56] 0 6 1 5 2 6 4 5 5 4 …
 $ fatal_accidents_00_14 : int [1:56] 0 1 0 0 0 2 1 1 1 0 …
 $ fatalities_00_14     : int [1:56] 0 88 0 0 0 337 158 7 88 0 …

   airline           incl_reg_subsidiaries avail_seat_km_per_week
 Length:56          Mode :logical          Min.   :2.594e+08
 Class :character    FALSE:40              1st Qu.:4.740e+08
 Mode  :character    TRUE :16              Median :8.029e+08
                                           Mean   :1.385e+09
                                           3rd Qu.:1.847e+09
                                           Max.   :7.139e+09
 incidents_85_99  fatal_accidents_85_99 fatalities_85_99 incidents_00_14
 Min.   : 0.000   Min.   : 0.000        Min.   :  0.0    Min.   : 0.000
 1st Qu.: 2.000   1st Qu.: 0.000        1st Qu.:  0.0    1st Qu.: 1.000
 Median : 4.000   Median : 1.000        Median : 48.5    Median : 3.000
 Mean   : 7.179   Mean   : 2.179        Mean   :112.4    Mean   : 4.125
 3rd Qu.: 8.000   3rd Qu.: 3.000        3rd Qu.:184.2    3rd Qu.: 5.250
 Max.   :76.000   Max.   :14.000        Max.   :535.0    Max.   :24.000
 fatal_accidents_00_14 fatalities_00_14
 Min.   :0.0000        Min.   :  0.00
 1st Qu.:0.0000        1st Qu.:  0.00
 Median :0.0000        Median :  0.00
 Mean   :0.6607        Mean   : 55.52
 3rd Qu.:1.0000        3rd Qu.: 83.25
 Max.   :3.0000        Max.   :537.00
```

112.410714285714

55.5178571428571

- Checking Missingness

```
[13]: sum(is.na(airline_safety))
      colSums(is.na(airline_safety))
```

0

airline   0 **incl_reg_subsidiaries**   0 **avail_seat_km_per_week**   0
incidents_85_99   0 **fatal_accidents_85_99**   0 **fatalities_85_99**   0
incidents_00_14   0 **fatal_accidents_00_14**   0 **fatalities_00_14**   0

- Checking Duplicates

```r
[14]: nrow(airline_safety)
      nrow(distinct(airline_safety))

      airline_safety %>%
        group_by(airline) %>%
        tally() %>%
        filter(n > 1)
```

56

56

A tibble: 0 × 2

airline	n
<chr>	<int>

```r
[15]: airline_safety %>%
        group_by(incl_reg_subsidiaries) %>%
        tally() %>%
        arrange(desc(n))
```

A tibble: 2 × 2

incl_reg_subsidiaries	n
<lgl>	<int>
FALSE	40
TRUE	16

Part II: Data Description (Codebook)

The airline_safety dataset contains safety records for 56 airlines from 1985–2014. The data were originally compiled by FiveThirtyEight and include operational exposure (airline size) and incident/fatality counts for two time periods. No missing values are present in this dataset.

Variable	Type	Description
airline	character	Airline name
incl_reg_subsidiaries	logical	TRUE if safety numbers include regional subsidiaries, otherwise FALSE
avail_seat_km_per_week	numeric	Airline size, measured as available seat–kilometers flown per week
incidents_85_99	integer	Total incidents from 1985–1999
fatal_accidents_85_99	integer	Fatal accidents from 1985–1999
fatalities_85_99	integer	Total fatalities from 1985–1999
incidents_00_14	integer	Total incidents from 2000–2014

Variable	Type	Description
fatal_accidents_00_14	integer	Fatal accidents from 2000–2014
fatalities_00_14	integer	Total fatalities from 2000–2014

Part III: Data Analysis/Visualization

Question 1. Which airlines have the highest total number of incidents between 1985 and 2014, and what is the range of total incidents across all airlines?

```
[16]: airline_safety$total_incidents <- airline_safety$incidents_85_99 +
      airline_safety$incidents_00_14

      p3 <- ggplot(
      airline_safety,
      aes(x = reorder(airline, total_incidents), y = total_incidents)

      ) +
      geom_col() +
      coord_flip() +
      labs(
      title = "Total Incidents per Airline (1985-2014)",
      x = "Airline",
      y = "Total Incidents"
      ) +
      theme_minimal()

      ggsave("plot3_total_incidents_bar.png", p3, width = 6, height = 6)

      print(p3)
```
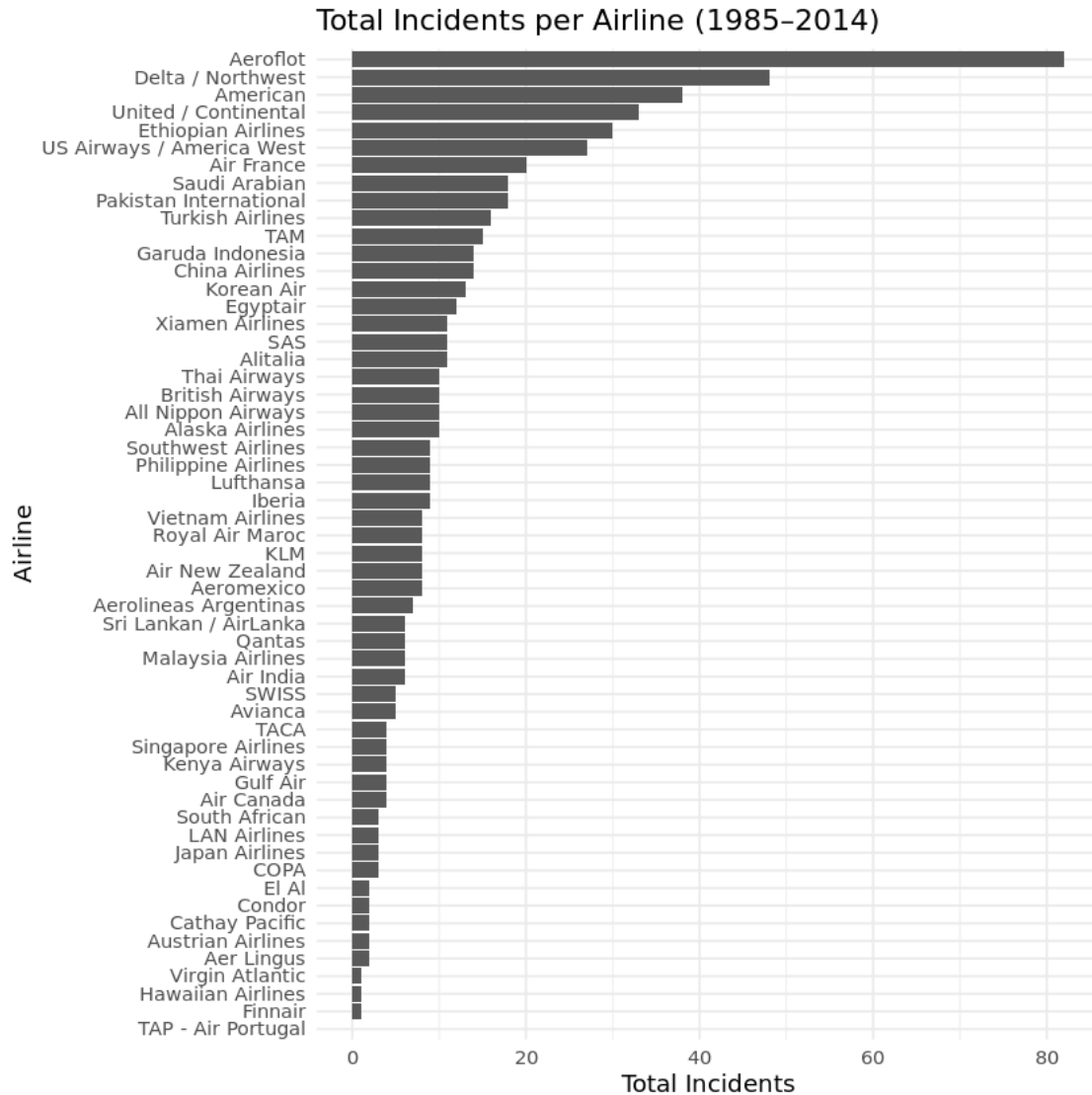
Total Incidents per Airline (1985–2014)

Figure 1. Horizontal bar chart displaying the Total Incidents recorded for each of the 56 airlines over the entire 30-year study period (1985–2014), sorted in descending order of incident count.

Conclusion: The bar chart of "Total Incidents per Airline (1985-2014)" shows that Aeroflot had the highest total number of incidents in the 30-year period. The next highest incidents belong to Delta/Northwest, American, and United/Continental. The total number of incidents across all 56 airlines ranges significantly, from a minimum of 0 for TAP Air Portugal to the maximum value of 76 for Aeroflot.

```
[17]: library(dplyr)

      airline_safety <- airline_safety %>%
          mutate(
              incidents_85_99_rate = incidents_85_99 / (avail_seat_km_per_week / 1e9),
```

```
        incidents_00_14_rate = incidents_00_14 / (avail_seat_km_per_week / 1e9)
    )
```

Question 2. Which airlines have the highest incident rates?

[18]:
```
install.packages('ggrepel')
```

Installing package into '/srv/rlibs'
(as 'lib' is unspecified)

[19]:
```
library(ggplot2)
library(ggrepel)

p1 <- ggplot(
    airline_safety,
    aes(
        x = avail_seat_km_per_week,
        y = incidents_85_99_rate,
        label = airline
    )
) +
    geom_point() +
    geom_text(aes(label = airline),
            vjust = -0.5,
            size = 3
    ) +
    labs(
        title = "Incident Rate (1985-1999) vs Operational Volume",
        x = "Available Seat KM per Week",
        y = "Incidents per Billion Seat-KM (1985-1999)"
    ) +
    theme_minimal()

print(p1)
```
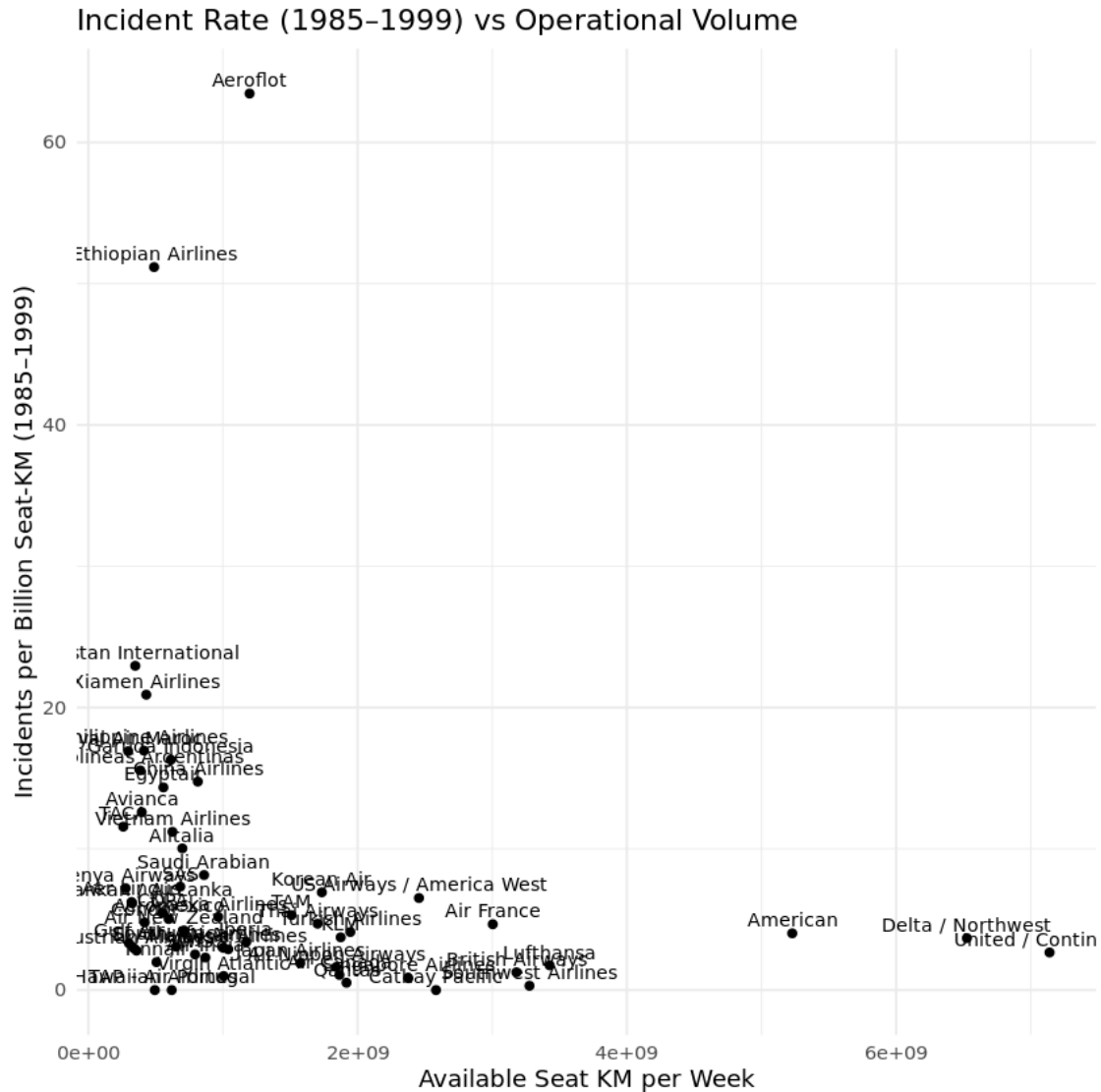
Figure 2. This scatterplot displays the relationship between each airline's operational volume, measured as available seat-kilometers per week, and its incident rate during 1985–1999, expressed per billion seat-kilometers.

```
[20]: p2 <- ggplot(
          airline_safety,
          aes(
              x = avail_seat_km_per_week,
              y = incidents_00_14_rate,
              label = airline
          )
      ) +
```

```
    geom_point() +
    geom_text(aes(label = airline),
          vjust = -0.5,
          size = 3)  +
    labs(
        title = "Incident Rate (2000-2014) vs Operational Volume",
        x = "Available Seat KM per Week",
        y = "Incidents per Billion Seat-KM (2000-2014)"
    ) +
    theme_minimal()

print(p2)
```
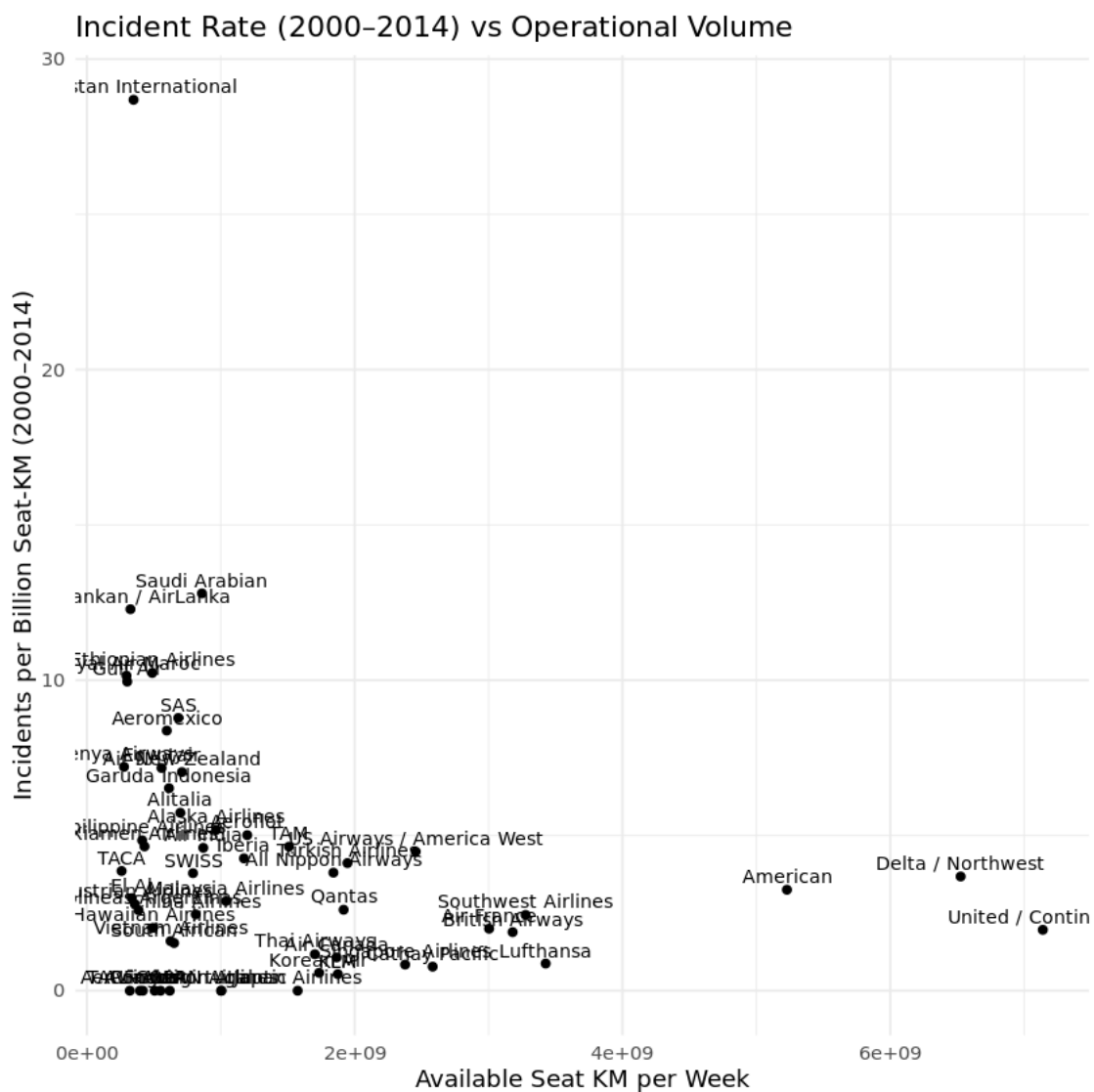

Incident Rate (2000–2014) vs Operational Volume

Figure 3. This scatterplot displays the relationship between each airline's operational volume, measured as available seat-kilometers per week, and its incident rate during 2000-2014, expressed per billion seat-kilometers.

Conclusion: The incident rate scatterplots reveal that the highest incident rates are generally associated with lower operational volume (Available Seat KM per Week). For the period 1985–1999, Aeroflot had the highest incident rate, followed by Ethiopian Airlines and Pakistan International. For the period 2000–2014, Pakistan International had the highest rate, followed by Saudi Arabian and Sri Lankan/AirLanka. Notably, Aeroflot's incident rate appears to have dropped significantly in the second period, moving from the highest rate in 1985–1999 to a much lower, clustered position in 2000–2014. Conversely, American, Delta/Northwest, and United/Continental maintain low incident rates relative to their high operational volume in both periods.

Question 3. How consistently did safety improvements occur across airlines from 1985–1999 to 2000–2014 after adjusting for operational volume?

```
[34]: library(dplyr)
      library(tibble)

      airline_safety <- airline_safety %>%
        mutate(
          incidents_85_99_rate       = incidents_85_99        /␣
       ↪(avail_seat_km_per_week / 1e9),
          fatal_accidents_85_99_rate = fatal_accidents_85_99 /␣
       ↪(avail_seat_km_per_week / 1e9),
          fatalities_85_99_rate      = fatalities_85_99        /␣
       ↪(avail_seat_km_per_week / 1e9),

          incidents_00_14_rate       = incidents_00_14        /␣
       ↪(avail_seat_km_per_week / 1e9),
          fatal_accidents_00_14_rate = fatal_accidents_00_14 /␣
       ↪(avail_seat_km_per_week / 1e9),
          fatalities_00_14_rate      = fatalities_00_14        /␣
       ↪(avail_seat_km_per_week / 1e9)
        )
```

```
[35]: p2 <- ggplot(
          airline_safety,
          aes(x = fatalities_85_99_rate,
              y = fatalities_00_14_rate,
              label = airline)
      ) +
          geom_point() +
          geom_text(
              vjust = -0.5,
              size = 3
          ) +
          labs(
```

```
        title = "Fatality Rates: 1985-1999 vs 2000-2014 (Standardized by SKM)",
        x = "Fatality Rate 1985-1999",
        y = "Fatality Rate 2000-2014"
    ) +
    theme_minimal()

ggsave("plot2_fatality_rates_comparison.png", p2, width = 6, height = 4)

print(p2)
```


Figure 4. Scatterplot comparing the raw number of fatalities between the period 1985–1999 (x-axis) and 2000–2014 (y-axis). This visualization helps identify airlines that experienced a change in the total number of fatalities between the two time periods.

10

Analysis Method 1: Dimensionality Reduction

```
[36]: airline_safety$class <- cut(
        airline_safety$fatalities_00_14_rate,
        breaks = c(-Inf, 0, 2, Inf),
        labels = c("none", "low", "high")
      )

      airline_safety$class <- as.factor(airline_safety$class)

      sapply(airline_safety, class)
```

airline 'character' **incl_reg_subsidiaries** 'logical' **avail_seat_km_per_week** 'numeric' **incidents_85_99** 'integer' **fatal_accidents_85_99** 'integer' **fatalities_85_99** 'integer' **incidents_00_14** 'integer' **fatal_accidents_00_14** 'integer' **fatalities_00_14** 'integer' **fatal_accidents_85_99_rate** 'numeric' **fatalities_85_99_rate** 'numeric' **fatal_accidents_00_14_rate** 'numeric' **fatalities_00_14_rate** 'numeric' **class** 'factor' **incidents_85_99_rate** 'numeric' **incidents_00_14_rate** 'numeric'

```
[37]: sapply(
        airline_safety %>% select(where(is.numeric)),
        function(x) {
          c(
            Mean = mean(x),
            SD   = sd(x),
            Var  = var(x),
            Min  = min(x),
            Max  = max(x)
          )
        }
      )
```

		avail_seat_km_per_week	incidents_85_99	fatal_accidents_85_99	fa
A matrix: 5 × 13 of type dbl	Mean	1.384621e+09	7.178571	2.178571	1
	SD	1.465317e+09	11.035656	2.861069	1
	Var	2.147154e+18	121.785714	8.185714	2
	Min	2.593733e+08	0.000000	0.000000	0.
	Max	7.139291e+09	76.000000	14.000000	5

```
[40]: airline_scaled <- airline_safety %>%
        mutate(across(
          .cols = where(is.numeric),
          .fns  = ~ as.numeric(scale(.))
        ))
```

```
[41]: airline_numeric <- airline_scaled %>%
        select(
```

```
    incidents_85_99_rate,
    fatal_accidents_85_99_rate,
    fatalities_85_99_rate,
    incidents_00_14_rate,
    fatal_accidents_00_14_rate,
    fatalities_00_14_rate
  )
```

[42]:
```
airline_pca <- prcomp(
   airline_numeric,
   center = FALSE,
   scale. = FALSE
)

summary(airline_pca)
airline_pca$rotation
```

```
Importance of components:
                          PC1    PC2    PC3     PC4     PC5    PC6
Standard deviation     1.6948 1.2464 0.8236 0.76597 0.41874 0.3658
Proportion of Variance 0.4787 0.2589 0.1130 0.09779 0.02922 0.0223
Cumulative Proportion  0.4787 0.7377 0.8507 0.94848 0.97770 1.0000
```

		PC1	PC2	PC3	PC4
	incidents_85_99_rate	0.4534195	0.2620169	0.60339132	0.10198439
	fatal_accidents_85_99_rate	0.4789720	0.3838092	0.21237815	-0.08083012
A matrix: 6 × 6 of type dbl	fatalities_85_99_rate	0.3779975	0.3060301	-0.60239564	-0.56383010
	incidents_00_14_rate	0.4268943	-0.1328973	-0.44871505	0.71068383
	fatal_accidents_00_14_rate	0.4322747	-0.4836178	0.01518499	-0.01321358
	fatalities_00_14_rate	0.2302484	-0.6624465	0.16235194	-0.39989397

[43]:
```
pc_scores <- as_tibble(airline_pca$x) %>%
   mutate(class = airline_safety$class)
```

[44]:
```
ggplot(pc_scores, aes(x = PC1, y = PC2, color = class, label =␣
 ↪airline_safety$airline)) +
     geom_point() +
   geom_text(aes(label = airline_safety$airline),
           vjust = -0.5,
           size = 3
   ) +
   labs(
     title = "PCA of Airline Safety Data",
     x = "Principal Component 1",
     y = "Principal Component 2",
     color = "Risk Class"
   ) +
```

```
    theme_minimal() +
    coord_fixed()
```

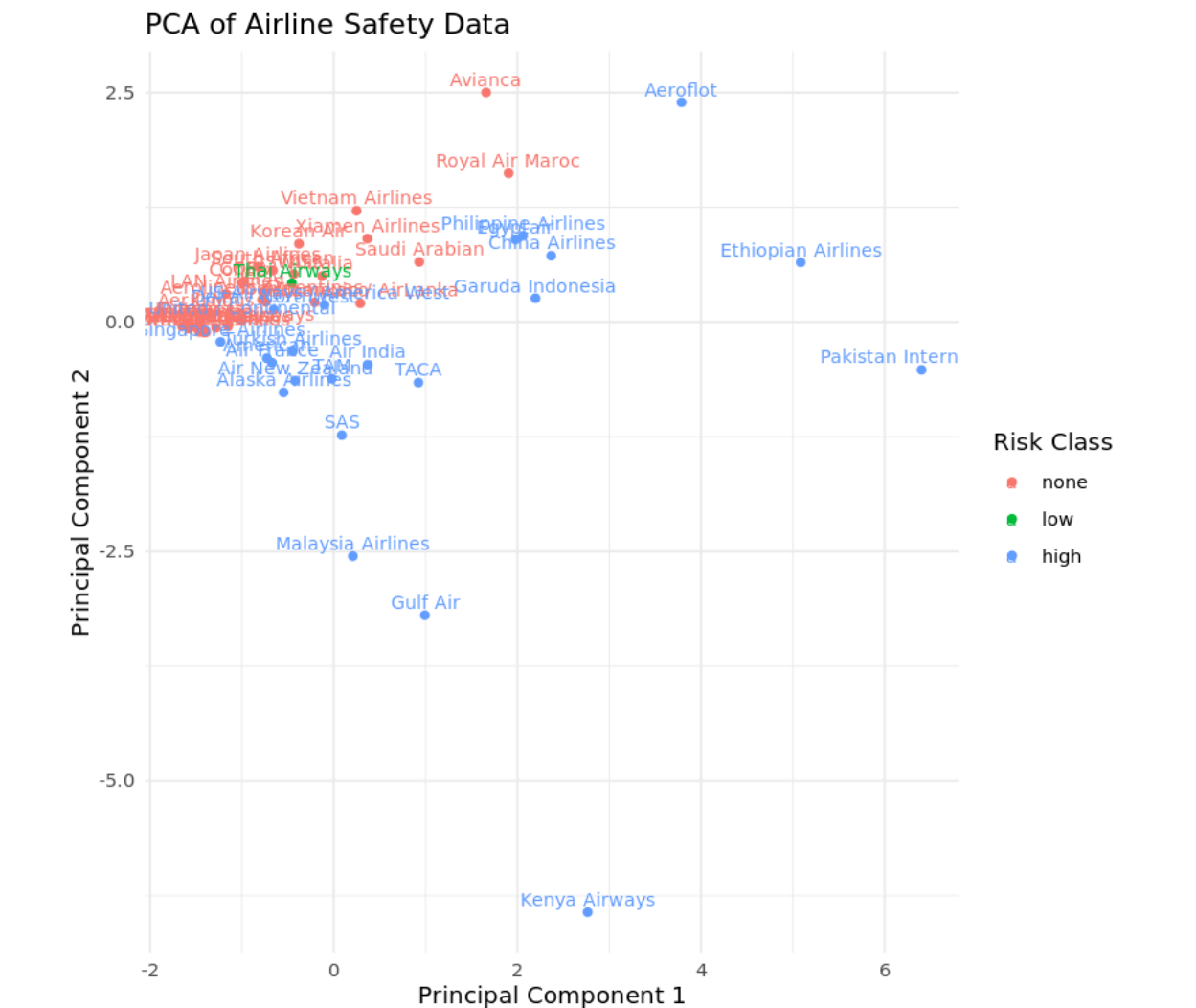### PCA of Airline Safety Data

Figure 5.

Analysis Method 2: Clustering

```
[45]: label_randomly <- function(n_points, n_clusters){
        sample(1:n_clusters, size = n_points, replace = TRUE)
      }

      get_cluster_means <- function(data, labels){
        data %>%
          mutate(label__ = labels) %>%
```

```r
      group_by(label__) %>%
      summarize(across(where(is.numeric), mean), .groups = "drop") %>%
      rename(label = label__) %>%
      arrange(label)
}

assign_cluster <- function(data, means){
  X <- as.matrix(data)
  C <- as.matrix(means %>% select(-label))
  X_sq <- rowSums(X*X)
  C_sq <- rowSums(C*C)
  dist_sq_matrix <- outer(X_sq, C_sq, "+") - 2*(X %*% t(C))
  max.col(-dist_sq_matrix)
}

kmeans_done <- function(old_means, new_means, eps = 1e-6){
  om <- as.matrix(old_means %>% select(-label))
  nm <- as.matrix(new_means %>% select(-label))
  mean(sqrt(rowSums((om - nm)^2))) < eps
}

mykmeans <- function(data, n_clusters, eps = 1e-6, max_iter = 100){
  labels <- label_randomly(nrow(data), n_clusters)
  old_means <- get_cluster_means(data, labels)
  iter <- 0
  repeat {
    labels <- assign_cluster(data, old_means)
    new_means <- get_cluster_means(data, labels)
    if (kmeans_done(old_means, new_means, eps) || iter >= max_iter) break
    old_means <- new_means
    iter <- iter + 1
  }
  if (iter >= max_iter) warning("K-means did not converge in max_iter.")
  cat("K-means converged after", iter, "iterations.\n")
  list(labels = labels, means = new_means)
}
```

```r
[46]: n_clusters <- 3
      my_results <- mykmeans(airline_numeric, n_clusters)

      print("--- Custom mykmeans Results (Cluster Labels) ---")
      print(my_results$labels)

      print("--- Custom mykmeans Results (Cluster Means) ---")
      print(my_results$means)
```

K-means converged after 4 iterations.

```
[1] "--- Custom mykmeans Results (Cluster Labels) ---"
 [1] 2 1 2 2 2 2 2 2 2 2 2 2 2 1 2 2 1 2 2 2 1 2 1 2 1 3 2 2 2 3 2 2 2 2 3 1 1 2
[39] 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
[1] "--- Custom mykmeans Results (Cluster Means) ---"
# A tibble: 3 × 7
  label incidents_85_99_rate fatal_accidents_85_99_rate fatalities_85_99_rate
  <int>                <dbl>
<dbl>                <dbl>
1     1                 1.58                       2.00
1.57
2     2               -0.302
-0.363
-0.278
3     3               -0.309
-0.667
-0.619
#   3 more variables: incidents_00_14_rate <dbl>,
#   fatal_accidents_00_14_rate <dbl>, fatalities_00_14_rate <dbl>
```

[47]:
```r
airline_matrix <- as.matrix(airline_numeric)

r_results <- kmeans(airline_matrix, centers = n_clusters, nstart = 25)

print("--- R's K-means Cluster Labels ---")
print(r_results$cluster)

print("--- R's K-means Means ---")
print(r_results$centers)
```

```
[1] "--- R's K-means Cluster Labels ---"
 [1] 3 2 3 3 3 3 3 3 3 3 3 3 3 3 2 3 3 2 3 3 3 2 3 2 3 2 1 3 3 3 1 3 3 3 3 1 2 2 3
[39] 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
[1] "--- R's K-means Means ---"
  incidents_85_99_rate fatal_accidents_85_99_rate fatalities_85_99_rate
1           -0.3092078                 -0.6670213            -0.6190439
2            1.5785394                  1.9983701             1.5661191
3           -0.3018007                 -0.3632788            -0.2781350
  incidents_00_14_rate fatal_accidents_00_14_rate fatalities_00_14_rate
1            0.5469733                  2.1942863             3.6196243
2            0.9006838                  0.8719603             0.1000995
3           -0.2215244                 -0.3279659            -0.2672675
```

[48]:
```r
library(ggplot2)

pc_cluster_plot <- pc_scores %>%
  mutate(cluster = as.factor(my_results$labels))
```

15

```r
ggplot(pc_cluster_plot, aes(PC1, PC2, color = cluster, label =␣
 ↪airline_safety$airline)) +
     geom_point() +
     geom_text(aes(label = airline_safety$airline),
          vjust = -0.5,
          size = 3
   ) +
 labs(
   title = "PCA of Airline Safety Data Colored by K-means Cluster",
   color = "Cluster"
 ) +
 theme_minimal()
```


PCA of Airline Safety Data Colored by K-means Cluster
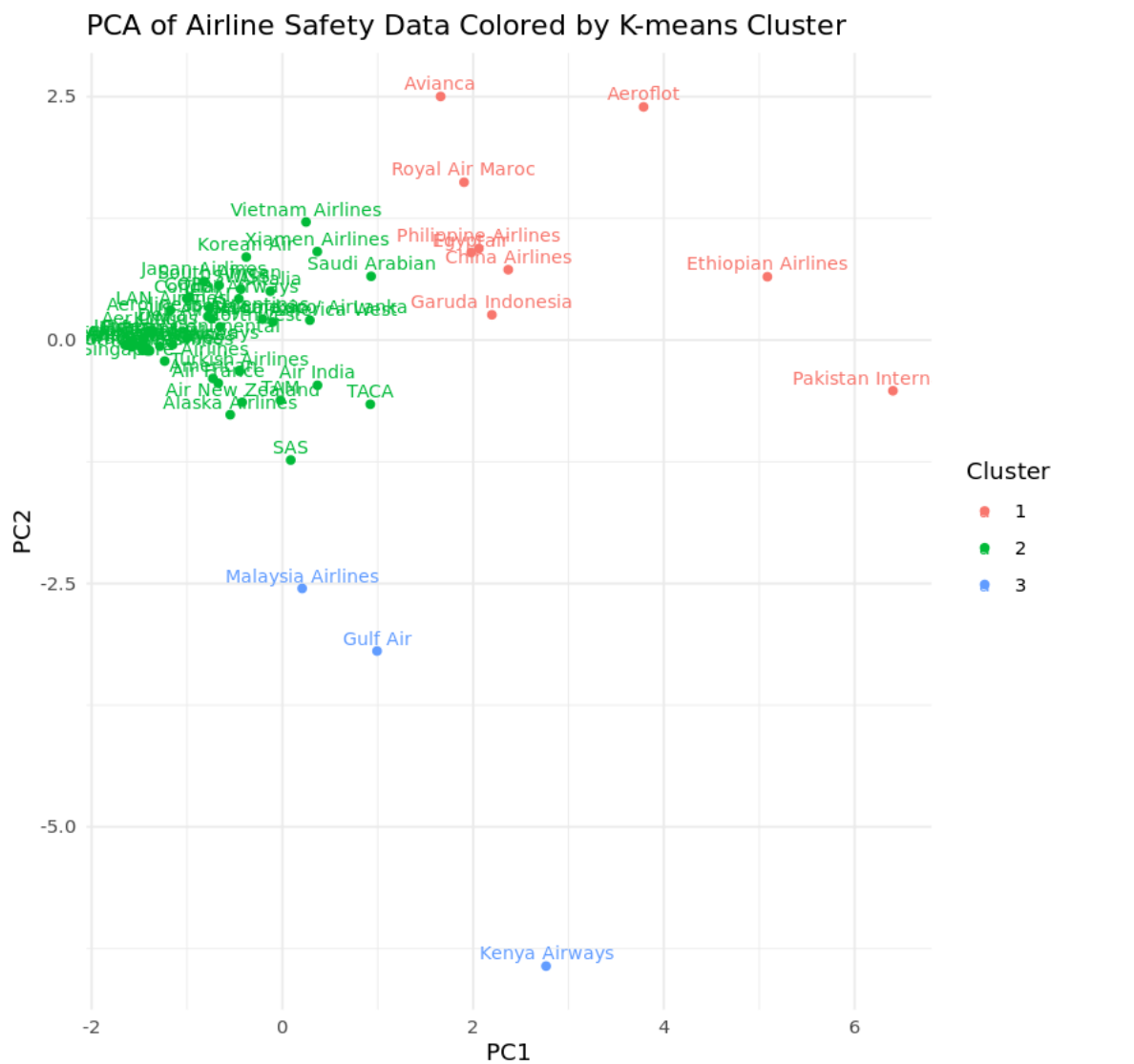
Figure 6.

Analysis Method 1: Regression

```
[49]: d <- airline_numeric
      d$airline <- airline_safety$airline

      glimpse(d)
      summary(d)

      set.seed(123)
      train <- runif(nrow(d)) < 0.75
      test  <- !train

      f_model <- fatalities_00_14_rate ~
          incidents_85_99_rate +
          fatal_accidents_85_99_rate +
          fatalities_85_99_rate +
          incidents_00_14_rate +
          fatal_accidents_00_14_rate

      m_improve <- lm(f_model, data = d %>% filter(train))
      summary(m_improve)

      dx <- d %>% filter(test)
      dx <- dx %>% mutate(pred_fatal_rate = predict(m_improve, dx))

      ggplot(dx, aes(x = fatalities_00_14_rate,
                     y = pred_fatal_rate,
                     label = airline)) +

        geom_point() +
        geom_text(vjust = -0.5, size = 3) +

        labs(
          x = "Actual Fatality Rate (00-14)",
          y = "Predicted Fatality Rate (00-14)",
          title = "Predicted vs Actual Fatality Rates (00-14)"
        ) +
        theme_minimal()

      ggplot(dx, aes(x = fatalities_00_14_rate - pred_fatal_rate)) +
        geom_density(fill = "coral", alpha = 0.5) +
        labs(
          x = "Residuals (Actual - Predicted Fatality Rate)",
          y = "Density",
          title = "Residual Density Plot (Fatality Rate Model)"
        ) +
```

```
    theme_minimal()
```

Rows: 56
Columns: 7
$ incidents_85_99_rate   <dbl> -0.1510810, 4.9876633,
0.6858237, -0.259392…
$ fatal_accidents_85_99_rate <dbl> -0.77289269, 3.08524002,
-0.77289269, -0.21…
$ fatalities_85_99_rate   <dbl> -0.6758657, -0.1190439,
-0.6758657, -0.1172…
$ incidents_00_14_rate   <dbl> -0.87882643, 0.18990017,
-0.32587492, 0.908…
$ fatal_accidents_00_14_rate <dbl> -0.5522797003,
0.0002180767, -0.5522797003,…
$ fatalities_00_14_rate   <dbl> -0.38717841, 0.05192897,
-0.38717841, -0.38…
$ airline   <chr> "Aer Lingus", "Aeroflot",
"Aerolineas Argen…

 incidents_85_99_rate fatal_accidents_85_99_rate fatalities_85_99_rate
 Min.   :-0.7107   Min.   :-0.7729   Min.   :-0.6759
 1st Qu.:-0.4891   1st Qu.:-0.7729   1st Qu.:-0.6759
 Median :-0.3118   Median :-0.3449   Median :-0.4905
 Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000
 3rd Qu.: 0.0628   3rd Qu.: 0.1742   3rd Qu.: 0.2790
 Max.   : 4.9877   Max.   : 3.0852   Max.   : 3.5639
 incidents_00_14_rate fatal_accidents_00_14_rate fatalities_00_14_rate
 Min.   :-0.8788   Min.   :-0.5523   Min.   :-0.3872
 1st Qu.:-0.6606   1st Qu.:-0.5523   1st Qu.:-0.3872
 Median :-0.2529   Median :-0.5523   Median :-0.3872
 Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000
 3rd Qu.: 0.1990   3rd Qu.: 0.1521   3rd Qu.:-0.1619
 Max.   : 5.2415   Max.   : 4.2183   Max.   : 5.7094
   airline
 Length:56
 Class :character
 Mode :character

Call:
lm(formula = f_model, data = d %>% filter(train))

Residuals:
    Min   1Q Median   3Q   Max
-2.1574 -0.2410 -0.1021 0.2128 1.7337
```

```
Coefficients:
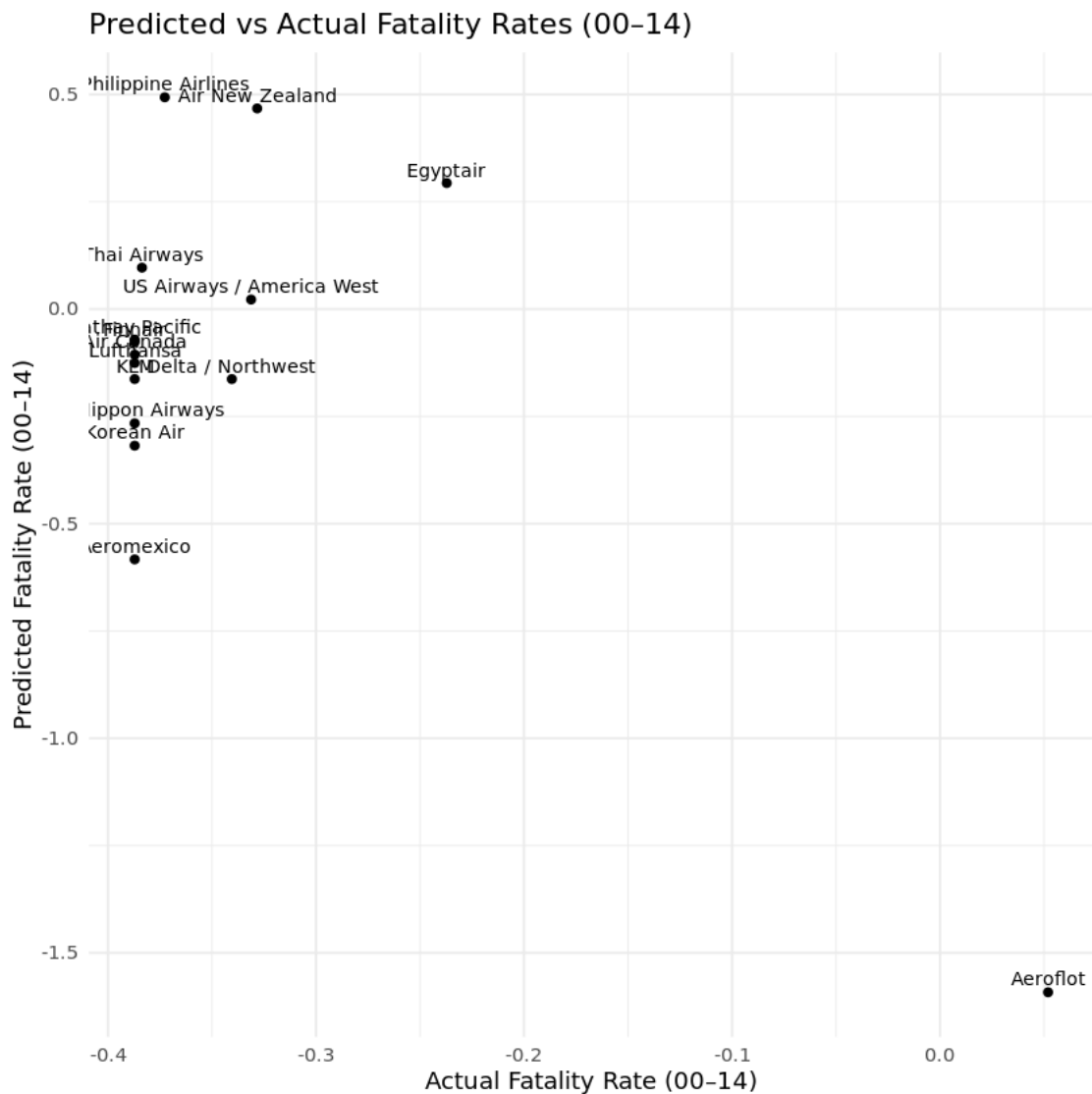                           Estimate Std. Error t value Pr(>|t|)
(Intercept)                 0.05264    0.11513   0.457    0.650
incidents_85_99_rate       -0.22765    0.23799  -0.957    0.345
fatal_accidents_85_99_rate -0.15132    0.24225  -0.625    0.536
fatalities_85_99_rate       0.02293    0.14869   0.154    0.878
incidents_00_14_rate       -0.20880    0.13688  -1.525    0.136
fatal_accidents_00_14_rate  0.97016    0.13154   7.376 1.26e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7281 on 35 degrees of freedom
Multiple R-squared:  0.6466,        Adjusted R-squared:  0.5961
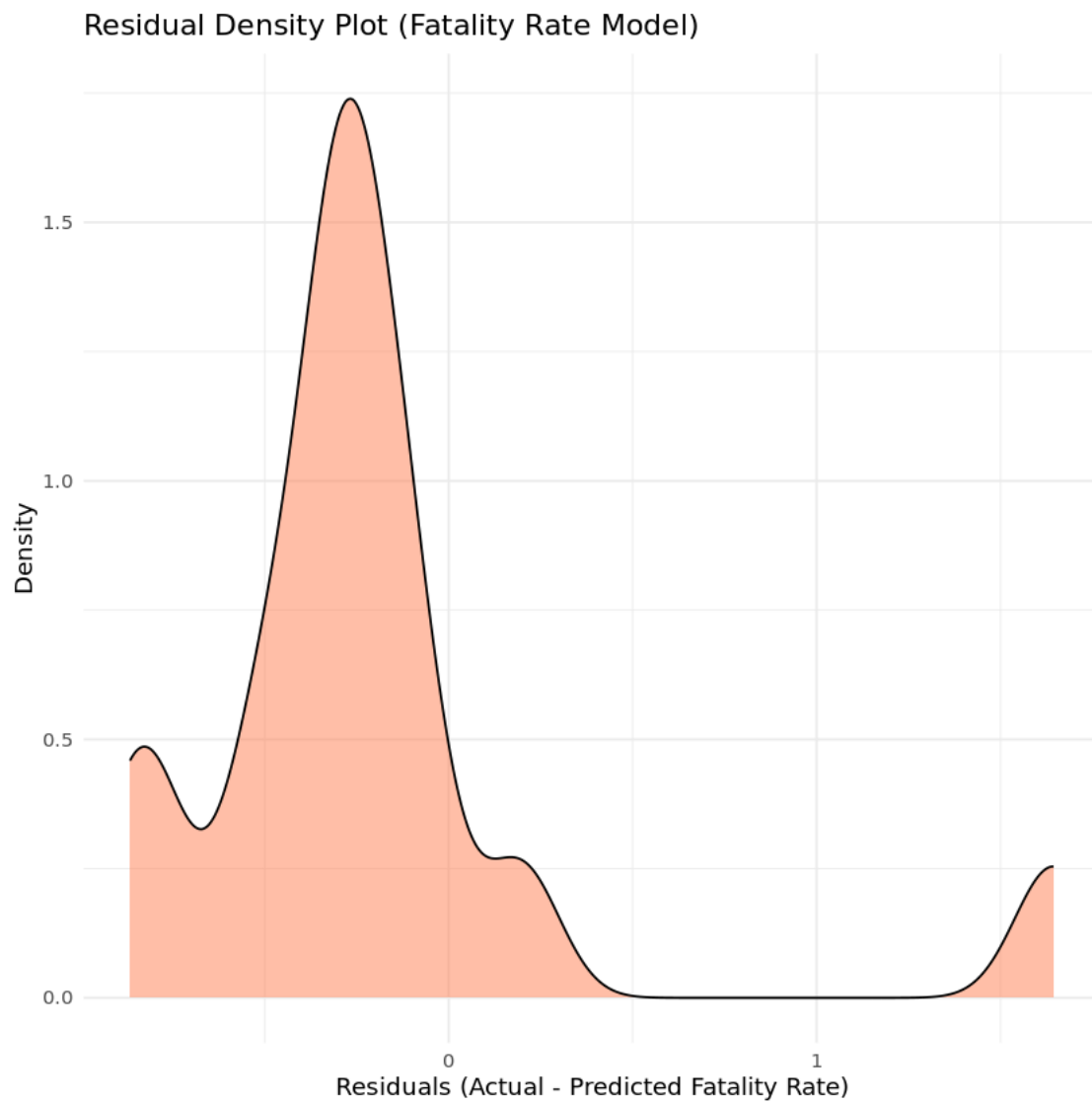F-statistic: 12.81 on 5 and 35 DF,  p-value: 4.122e-07
```


Predicted vs Actual Fatality Rates (00–14)

Residual Density Plot (Fatality Rate Model)

Figure 7.

Conclusion:

Next Steps:

[ ]: