# Impact of PM2.5 Exposure on Low Birth Weight in Ulaanbaatar (2016–2025)

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## ${\bf Contents}$

3 Exploratory Analysis 7 4 Analysis 13 5 Results and Interpretation 14 6 Conclusion and Policy Implications 15	1	Rationale and Research Questions	4
4 Analysis 13 5 Results and Interpretation 14 6 Conclusion and Policy Implications 15 7 References 16	2	Dataset Information	5
5 Results and Interpretation 14 6 Conclusion and Policy Implications 15 7 References 16	3	Exploratory Analysis	7
6 Conclusion and Policy Implications 15 7 References 16	4	Analysis	13
7 References 16	5	Results and Interpretation	14
	6	Conclusion and Policy Implications	15
<pre>knitr::opts_knit\$set(root.dir = here::here())</pre>	7	References	16
	kn		

# List of Tables

1	Summary of Birth Outcomes	11
2	Summary of Monthly PM2.5 Exposure	12

# List of Figures

1	Daily PM2.5 Concentrations ( $\mu g/m^3$ )	7
2	Number of Months with Missing PM2.5 Data by Year	8
3	Distribution of Monthly PM2.5 Concentrations	9
4	Low Birth Weight Rate vs. Monthly PM2.5	10

#### 1 Rationale and Research Questions

Exposure timing plays a key role in identifying how air pollution affects birth outcomes. Our initial analysis showed a weak and non-significant association between monthly PM2.5 levels and low birth weight rates (p = 0.113). This limited result likely occurred because measuring air pollution in the same month as birth ignores the critical periods during pregnancy when exposure actually affects fetal growth.

To address this, we will use lagged regression methods. These align PM2.5 exposure data with biologically relevant periods—like the second and third trimesters—when exposure most impacts fetal development. This approach helps reduce confounding from seasonal variations and reveals the true health impacts of PM2.5 on birth outcomes.

Research Questions: 1. Does prenatal exposure to PM2.5 affect the incidence of low birth weight (LBW) in Ulaanbaatar? 2. Which gestational periods (measured as lags) show the strongest associations between PM2.5 and LBW? 3. Are cumulative exposures over multiple months more predictive than single-month lags?

#### 2 Dataset Information

```
# Read birth weight and live births data
birth weight low <- read.csv(here("Data/Raw/BIRTH WEIGTH LOWER THAN 2500 GRAMS.csv"), stringsAsFactors
live_births <- read.csv(here("./Data/Raw/LIVE BIRTHS.csv"), stringsAsFactors = TRUE)</pre>
# Clean live births
live births clean <- live births
for (col in names(live_births_clean)[-1]) {
  live_births_clean[[col]] <- as.numeric(gsub(",", "", live_births_clean[[col]]))</pre>
# Convert wide to long format
birth_weight_low_long <- birth_weight_low %>%
  pivot_longer(-Aimag, names_to = "Month", values_to = "Low_Birth_Weight")
live_births_long <- live_births_clean %>%
  pivot_longer(-Aimag, names_to = "Month", values_to = "Live_Births")
# Remove 'X' from month names
birth_weight_low_long <- birth_weight_low_long %>% mutate(Month = gsub("^X", "", Month))
                     <- live_births_long %>% mutate(Month = gsub("^X", "", Month))
live_births_long
# Merge datasets and create Date column
births merged <- left join(birth weight low long, live births long, by = c("Aimag", "Month")) %>%
  mutate(Date = ym(Month)) %>%
  select(Aimag, Date, Low_Birth_Weight, Live_Births)
# Load and clean PM2.5 data
years <- 2015:2025
pm25_files <- paste0(here("Data", "Raw"), "/Ulaanbaatar_PM2.5_", years, "_YTD.csv")
names(pm25_files) <- years</pre>
pm25_all <- map_dfr(pm25_files, read_csv, show_col_types = FALSE) %>%
  mutate(across(where(is.numeric), ~ na_if(., -999))) %>%
  clean names() %>%
  rename(DateTime = date_lt) %>%
  mutate(DateTime = parse date time(DateTime, orders = "ymd IMp"), Date = date(DateTime))
# Aggregate PM2.5 data
pm25_daily <- pm25_all %>%
  mutate(Date = date(DateTime)) %>%
  group_by(Date) %>%
  summarize(
    raw_conc_daily = mean(raw_conc, na.rm = TRUE),
    aqi_daily = mean(aqi, na.rm = TRUE),
   hours_reported = n(),
    hours_missing_raw = sum(is.na(raw_conc)),
   hours_missing_aqi = sum(is.na(aqi)),
    .groups = "drop"
  ) %>%
  mutate(DateTime = as datetime(Date))
```

```
pm25_monthly <- pm25_daily %>%
  mutate(Month = floor_date(Date, "month")) %>%
  group_by(Month) %>%
  summarize(
   raw_conc_monthly = mean(raw_conc_daily, na.rm = TRUE),
    aqi_monthly = mean(aqi_daily, na.rm = TRUE),
    days_reported = n(),
    days_missing_raw = sum(is.na(raw_conc_daily)),
   days_missing_aqi = sum(is.na(aqi_daily)),
    .groups = "drop"
  ) %>%
  mutate(DateTime = as_datetime(Month))
# Merge with birth data
full_data <- births_merged %>%
  left_join(pm25_monthly, by = c("Date" = "Month")) %>%
  arrange(Date)
```

#### 3 Exploratory Analysis

0

2016

```
ggplot(pm25_daily, aes(x = Date, y = raw_conc_daily)) +
  geom_line() +
labs(
   title = "Daily PM2.5 Concentrations (µg/m³)",
   x = "Date",
   y = "Daily mean PM2.5"
) +
theme_minimal()
```

# Daily PM2.5 Concentrations (µg/m³) 600 23: 400 200

Figure 1: Daily PM2.5 Concentrations ( $\mu g/m^3$ )

2020

Date

2024

2022

2018

```
pm25_yearly_missing <- pm25_monthly %>%
  mutate(Year = year(Month)) %>%
  group_by(Year) %>%
  summarize(
   total_months = n(),
   months_with_missing_days = sum(days_missing_raw > 0),
   total_missing_days = sum(days_missing_raw),
   .groups = "drop"
)
```

```
ggplot(pm25_yearly_missing, aes(x = Year, y = months_with_missing_days)) +
  geom_col(fill = "tomato") +
  labs(
    title = "Number of Months with Missing PM2.5 Data by Year",
    x = "Year",
    y = "Months with 1 Missing Day"
  ) +
  theme_minimal()
```

#### Number of Months with Missing PM2.5 Data by Year

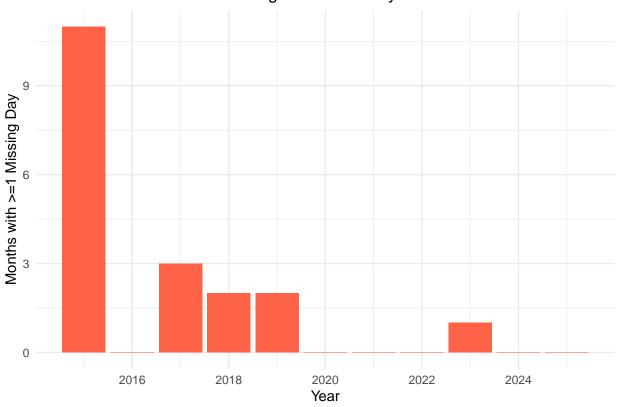


Figure 2: Number of Months with Missing PM2.5 Data by Year

```
ggplot(pm25_monthly, aes(y = raw_conc_monthly)) +
  geom_boxplot(outlier.colour = "red", outlier.shape = 1) +
  labs(
    title = "Distribution of Monthly PM2.5",
    y = "Monthly mean PM2.5 (µg/m³)"
  ) +
  theme_minimal()
```

```
# Compute low birth weight rate (Percentage)
full_data <- full_data %>% mutate(LBW_rate = 100 * Low_Birth_Weight / Live_Births)
ggplot(full_data, aes(x = raw_conc_monthly, y = LBW_rate)) +
```

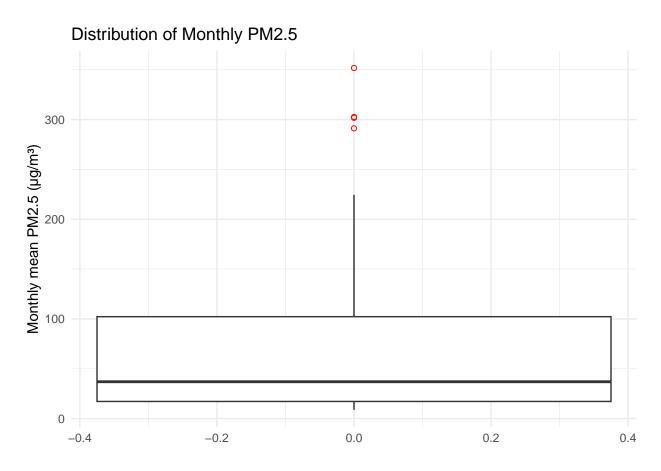


Figure 3: Distribution of Monthly PM2.5 Concentrations

```
geom_point() +
geom_smooth(method = "lm", se = TRUE, color = "blue") +
labs(
   title = "Low Birth Weight Rate vs. Monthly PM2.5",
   x = "PM2.5 (µg/m³)",
   y = "LBW Rate (Percentage)"
) +
theme_minimal()
```

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

#### Low Birth Weight Rate vs. Monthly PM2.5

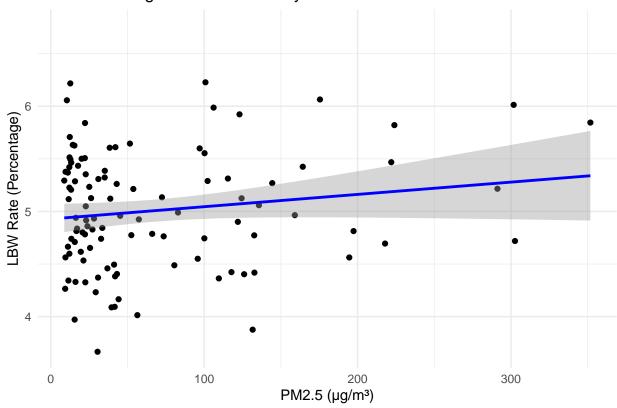


Figure 4: Low Birth Weight Rate vs. Monthly PM2.5

```
# Summary statistics for birth outcomes and PM2.5
births_summary <- full_data %>% summarise(
    Mean_LBW = mean(Low_Birth_Weight, na.rm = TRUE),
    Median_LBW = median(Low_Birth_Weight, na.rm = TRUE),
    Min_LBW = min(Low_Birth_Weight, na.rm = TRUE),
    Max_LBW = max(Low_Birth_Weight, na.rm = TRUE),
    SD_LBW = sd(Low_Birth_Weight, na.rm = TRUE),
    N_LBW = sum(!is.na(Low_Birth_Weight)),
    Mean_Live = mean(Live_Births, na.rm = TRUE),
    Median_Live = median(Live_Births, na.rm = TRUE),
    Min_Live = min(Live_Births, na.rm = TRUE),
```

```
Max_Live = max(Live_Births, na.rm = TRUE),
  SD_Live = sd(Live_Births, na.rm = TRUE),
 N_Live = sum(!is.na(Live_Births))
pm25_summary <- full_data %>% summarise(
 Mean_PM25 = mean(raw_conc_monthly, na.rm = TRUE),
 Median PM25 = median(raw conc monthly, na.rm = TRUE),
 Min_PM25 = min(raw_conc_monthly, na.rm = TRUE),
 Max_PM25 = max(raw_conc_monthly, na.rm = TRUE),
  SD_PM25 = sd(raw_conc_monthly, na.rm = TRUE),
  N_PM25 = sum(!is.na(raw_conc_monthly)),
  Mean_AQI = mean(aqi_monthly, na.rm = TRUE),
 Median_AQI = median(aqi_monthly, na.rm = TRUE),
 Min_AQI = min(aqi_monthly, na.rm = TRUE),
 Max_AQI = max(aqi_monthly, na.rm = TRUE),
 SD_AQI = sd(aqi_monthly, na.rm = TRUE),
 N_AQI = sum(!is.na(aqi_monthly))
# Summary tables
births_summary %>%
 t() %>% as.data.frame() %>%
 rownames_to_column("Statistic") %>%
 rename(Value = V1) %>%
 kable(caption = "Summary of Birth Outcomes", digits = 2) %>%
  kable_styling(full_width = FALSE)
```

Table 1: Summary of Birth Outcomes

Statistic	Value
${\rm Mean\_LBW}$	155.97
$Median\_LBW$	153.00
$Min\_LBW$	88.00
$Max\_LBW$	214.00
$SD\_LBW$	21.87
$N\_LBW$	111.00
$Mean\_Live$	3110.86
Median_Live	3187.00
Min_Live	1934.00
$Max\_Live$	3737.00
SD_Live	360.42
N_Live	111.00

```
pm25_summary %>%
  t() %>% as.data.frame() %>%
  rownames_to_column("Statistic") %>%
  rename(Value = V1) %>%
  kable(caption = "Summary of Monthly PM2.5 Exposure", digits = 2) %>%
  kable_styling(full_width = FALSE)
```

Table 2: Summary of Monthly PM2.5 Exposure

Statistic	Value
Mean_PM25	67.28
$Median\_PM25$	35.22
$Min\_PM25$	8.80
$Max\_PM25$	351.76
$SD\_PM25$	72.90
$N_{PM25}$	107.00
$Mean\_AQI$	111.86
$Median\_AQI$	92.67
$Min\_AQI$	31.73
$Max\_AQI$	274.00
SD_AQI	66.15
N_AQI	107.00

# 4 Analysis

5 Results and Interpretation

6 Conclusion and Policy Implications

# 7 References