# Walmart Store Distribution and Its Correlation with State GDP in the U.S.

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## Table of contents

1	Introduction	1		
2	Source and Background of the data 2.1 Walmart Store Distribution Data			
3	FAIR/CARE Principle	2		
4	Data Visualizations and Results	3		
5	Conclusion			
6	References			
7	Code Appendix 7.1 Store distribution table	8 9 10		
	7.5 A correlation test	11		

## 1 Introduction

This report analyzes the relationship between Walmart store distribution and economic activity (measured by GDP) across U.S. states. Walmart, as the largest retailer in the United States, strategically locates its stores based on demographic and economic factors. By examining

the correlation between the number of Walmart stores per state and state-level GDP, we aim to identify patterns in retail market penetration relative to economic output. Key questions include:

Do states with higher GDP have more Walmart stores?

Which states show the highest/lowest GDP per Walmart store?

Are there regional economic trends reflected in Walmart's distribution?

This analysis provides insights for business strategy, economic research, and retail market analysis.

## 2 Source and Background of the data

#### 2.1 Walmart Store Distribution Data

This data was found and tidied by Qianhui Dai. Source: The dataset lists the number of Walmart stores (total\_stores) per U.S. state (including territories like Puerto Rico and Washington, D.C.). Background: Walmart operates over 4,700 stores nationwide, with density influenced by population, income levels, and urbanization. States like Texas (595 stores) and Florida (386 stores) have the highest counts, reflecting their large populations and consumer demand.

#### 2.2 State GDP Data

This data was found and tidied by Joseph Easterday. Source: The dataset provides 2024 GDP estimates in millions of USD (GDP\_In\_Millions\_2024) for each state, sourced from official economic reports (e.g., U.S. Bureau of Economic Analysis). Background:GDP measures a state's economic output. High-GDP states like California (4.1 trillion) and Texas (2.7 trillion) drive national economic activity, while smaller economies(e.g., Vermont, Wyoming) may have different retail dynamics.

## 3 FAIR/CARE Principle

- 1. Cleaning and Structuring the data to meet the FAIR principle.
- a. Removed unnecessary header rows and renamed unclear column names.
- b. Standardized state names and abbreviations to ensure consistency across datasets.
- c. Converted numeric values from text to proper numeric formats for analysis.
- 2. Merging Datasets to let it be interoperable

- a. Merged Walmart store data with state GDP data using a common key, enabling us to analyze relationships across sources.
- b. Ensured coordinate and region data from Walmart were preserved to allow for geographic visualization and spatial analysis.
- 3. Creating Visual and Statistical Outputs to let it be reusable
- a. Generated scatter plots and bar plots to illustrate trends and patterns.
- b. Performed correlation analysis between GDP and Walmart distribution to uncover relationships.
- c. Plan to compile all steps into a reproducible Quarto report, so others can access and reuse our workflow.
- 4. Respecting CARE Principles
- a. Collective Benefit: The analysis may help identify economic development patterns and retail accessibility, benefiting researchers and policymakers.
- b. Authority to Control: We used publicly available data from Walmart official Website and official website of United States to respect the data ownership.
- c. Responsibility & Ethics: We ensured no personal or sensitive data was included, and we avoided drawing misleading conclusions from preliminary results.

#### 4 Data Visualizations and Results

In this project, we examined the relationship between Walmart store distribution across U.S. states and each state's gross domestic product (GDP). Using two datasets — one listing the number of Walmart stores per state, and another detailing state GDP — we created multiple visualizations to explore potential patterns and correlations between store counts and economic output.

#### # A tibble: 52 x 3

	StateName	${\tt StateAbbr}$	${\tt Stores}$
	<chr></chr>	<chr></chr>	<dbl></dbl>
1	Texas	TX	595
2	Florida	FL	386
3	California	CA	308
4	Georgia	GA	214
5	North Carolina	NC	214
6	Illinois	IL	177
7	Ohio	OH	172
8	Pennsylvania	PA	159
9	Missouri	MO	156

# i 42 more ro	NS.				
# A tibble: 51		GDD T W:11: 0004			
GeoName	StateAbbr	GDP_In_Millions_2024			
<chr></chr>	<chr></chr>	<dbl></dbl>			
1 Alabama	AL	321238.			
2 Alaska	AK	69969			
3 Arizona	AZ	552167			
4 Arkansas	AR	188723.			
5 California	CA	4103124.			
6 Colorado	CO	553322.			
7 Connecticut	CT	365723.			
8 Delaware	DE	103253.			
9 Florida	FL	1705565.			
10 Georgia	GA	882534.			
# i 41 more rows					

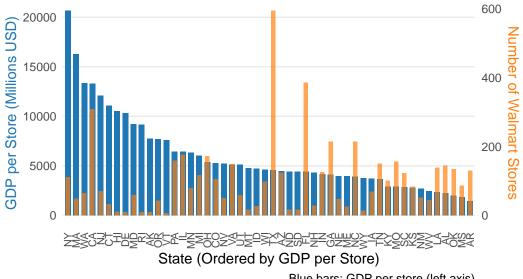
TN

10 Tennessee

150

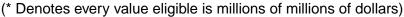
The bar plot revealed that states with higher GDP (e.g., California, Texas) tend to have a larger number of Walmart stores. However, some states with high GDP (like New York) did not have proportionally high Walmart store counts, suggesting regional market or policy differences.

## State GDP vs. Walmart Store Distribution



Blue bars: GDP per store (left axis) Orange bars: Number of stores (right axis) The scatter plot confirmed a moderate positive correlation between state GDP and the number of Walmart stores. This suggests that while GDP is a general predictor of store presence, it is not the only factor — other considerations like population density, land availability, and corporate strategy may influence store distribution.

State GDP vs. Walmart Store Distribution





These findings can help Walmart and other retailers assess potential markets for expansion based on economic indicators. By visualizing how store presence aligns with economic activity, decision-makers can identify underserved areas or prioritize states with untapped potential. Moreover, the Pearson correlation coefficient between state GDP and the number of Walmart stores is approximately 0.75, indicating a strong positive linear relationship. This suggests that, generally, states with higher economic output tend to host more Walmart locations.

\$pearson\$p\_value
[1] 3.750816e-10

\$pearson\$conf\_int
[1] 0.5955575 0.8505159
attr(,"conf.level")

[1] 0.95

\$spearman\$p\_value
[1] 8.025663e-13

\$correlation\_matrix

gdp stores gdp 1.0000000 0.7496365 stores 0.7496365 1.0000000

#### 5 Conclusion

In this project, we investigated the relationship between the number of Walmart stores in each U.S. state and the corresponding state-level GDP. By merging and analyzing data from Walmart's public store distribution and state GDP statistics, we aimed to explore whether economic strength correlates with retail presence.

Our visualizations — including a bar chart comparing store count and GDP by state, a scatter plot, and a correlation matrix — revealed a clear pattern: states with higher GDPs generally have more Walmart locations. Most notably, our correlation analysis showed a Pearson coefficient of 0.75, indicating a strong positive linear relationship between GDP and Walmart store count. This suggests that Walmart tends to concentrate stores in economically stronger states, likely due to higher consumer demand, infrastructure, and urban development.

While GDP proved to be a strong indicator, we acknowledge that it is not the sole factor influencing store distribution. States like New York and New Jersey, for example, showed lower-than-expected store counts despite having large economies — possibly due to high real estate costs, population density, or regional business strategies. Including population, land area, or urbanization metrics in future analyses could offer a more complete explanation.

Overall, our findings highlight how data visualization and correlation analysis can offer practical insights for business strategy, retail planning, and economic geography. This analysis may assist retailers or policy makers in identifying market opportunities or evaluating how commercial infrastructure aligns with economic activity.

## 6 References

Bureau of Economic Analysis. "GDP by State (Annual)". U.S. Department of Commerce, https://apps.bea.gov/itable/?ReqID=70&step=1.

Walmart Tech. "Walmart Store Status Public Dataset". Walmart Open Data Hub, https://walmart-open-data-walmarttech.opendata.arcgis.com/datasets/39ce1c357bd2424ca481db84aed29464\_0

## 7 Code Appendix

#### 7.1 Store distribution table

```
library(dplyr)
library(readxl)
library(writexl)
walmart_raw <- read_excel("~/Desktop/walmart_store_distribution.xlsx")</pre>
state_abbr_df <- tibble(</pre>
  StateName = c(
    "Alabama", "Alaska", "Arizona", "Arkansas",
    "California", "Colorado", "Connecticut", "Delaware",
    "Florida", "Georgia", "Hawaii", "Idaho",
    "Illinois", "Indiana", "Iowa", "Kansas",
    "Kentucky", "Louisiana", "Maine", "Maryland",
    "Massachusetts", "Michigan", "Minnesota", "Mississippi",
    "Missouri", "Montana", "Nebraska", "Nevada",
    "New Hampshire", "New Jersey", "New Mexico", "New York",
    "North Carolina", "North Dakota", "Ohio", "Oklahoma",
    "Oregon", "Pennsylvania", "Rhode Island", "South Carolina",
    "South Dakota", "Tennessee", "Texas", "Utah",
    "Vermont", "Virginia", "Washington", "West Virginia",
    "Wisconsin", "Wyoming"
  ),
  StateAbbr = c(
    "AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DE",
    "FL", "GA", "HI", "ID", "IL", "IN", "IA", "KS",
    "KY", "LA", "ME", "MD", "MA", "MI", "MN", "MS",
    "MO", "MT", "NE", "NV", "NH", "NJ", "NM", "NY",
    "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
```

```
"SD", "TN", "TX", "UT", "VA", "WA", "WA", "WV",
    "WI", "WY"
)

walmart_tidy <- walmart_raw %>%
    rename(Stores = total_stores) %>%
    left_join(state_abbr_df, by = c("state" = "StateAbbr")) %>%
    select(StateName, StateAbbr = state, Stores) %>%
    arrange(desc(Stores))

print(walmart_tidy)

write_xlsx(walmart_tidy, "~/Desktop/walmart_distribution_tidy.xlsx")
```

#### 7.2 State GDP table

```
library(dplyr)
library(readxl)
library(writexl)
raw_data <- read_excel("~/Downloads/Gross_Domestic_Product.xlsx", skip = 5)</pre>
cleaned_data <- raw_data %>%
  select(GeoFips, GeoName, `2024`) %>%
  filter(!GeoName %in% c("District of Columbia", "United States"))
state_abbr_df <- tibble(</pre>
  GeoName = c(
    "Alabama", "Alaska", "Arizona", "Arkansas",
    "California", "Colorado", "Connecticut", "Delaware",
    "Florida", "Georgia", "Hawaii", "Idaho",
    "Illinois", "Indiana", "Iowa", "Kansas",
    "Kentucky", "Louisiana", "Maine", "Maryland",
    "Massachusetts", "Michigan", "Minnesota", "Mississippi",
    "Missouri", "Montana", "Nebraska", "Nevada",
    "New Hampshire", "New Jersey", "New Mexico", "New York",
    "North Carolina", "North Dakota", "Ohio", "Oklahoma",
    "Oregon", "Pennsylvania", "Rhode Island", "South Carolina",
    "South Dakota", "Tennessee", "Texas", "Utah",
```

```
"Vermont", "Virginia", "Washington", "West Virginia",
    "Wisconsin", "Wyoming"
  ),
  StateAbbr = c(
    "AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DE",
    "FL", "GA", "HI", "ID", "IL", "IN", "IA", "KS",
    "KY", "LA", "ME", "MD", "MA", "MI", "MN", "MS",
    "MO", "MT", "NE", "NV", "NH", "NJ", "NM", "NY",
    "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
    "SD", "TN", "TX", "UT", "VT", "VA", "WA", "WV",
    "WI", "WY"
)
tidy_data <- cleaned_data %>%
  left_join(state_abbr_df, by = "GeoName") %>%
  group_by(GeoName, StateAbbr) %>%
  summarise(
    GDP_In_Millions_2024 = sum(`2024`, na.rm = TRUE),
    .groups = 'drop'
print(tidy_data)
write xlsx(tidy data, "~/Downloads/state statistics.xlsx")
```

## 7.3 Bar plot of GDP vs. number of Walmart store

```
library(readx1)
library(dplyr)
library(ggplot2)
library(scales)

gdp_data <- read_excel("desktop/state_statistics.xlsx") %>%
    select(State = StateAbbr, GDP = GDP_In_Millions_2024)

walmart_data <- read_excel("desktop/walmart_store_distribution.xlsx") %>%
    select(State = state, total_stores)

combined_data <- inner_join(gdp_data, walmart_data, by = "State")</pre>
```

```
combined_data <- combined_data %>%
 mutate(GDP_per_store = GDP / total_stores)
combined_data <- combined_data %>%
 arrange(desc(GDP_per_store))
ggplot(combined data, aes(x = reorder(State, -GDP per store))) +
 geom_bar(aes(y = GDP_per_store), stat = "identity", fill = "#1f77b4", width = 0.7) +
 geom_bar(aes(y = total_stores * max(GDP_per_store) / max(total_stores)),
           stat = "identity", fill = "#ff7f0e", alpha = 0.7, width = 0.5) +
 scale_y_continuous(
   name = "GDP per Store (Millions USD)",
   sec.axis = sec_axis(~ . * max(combined_data$total_stores) / max(combined_data$GDP_per_stores)
                        name = "Number of Walmart Stores")
 ) +
 labs(title = "State GDP vs. Walmart Store Distribution",
      x = "State (Ordered by GDP per Store)",
       caption = "Blue bars: GDP per store (left axis)\nOrange bars: Number of stores (right
 theme minimal() +
 theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5, size = 8),
       plot.title = element_text(hjust = 0.5, face = "bold"),
       axis.title.y = element_text(color = "#1f77b4"),
       axis.title.y.right = element_text(color = "#ff7f0e"),
       panel.grid.major.x = element_blank(),
       panel.grid.minor = element_blank())
```

#### 7.4 Scattered plot of GDP vs. number of Walmart store

```
library(readxl)
library(dplyr)
library(ggplot2)
library(scales)

walmart <- read_excel("desktop/walmart_store_distribution.xlsx")
state_stats <- read_excel("desktop/state_statistics.xlsx")

merged_data <- inner_join(walmart, state_stats, by = c("state" = "StateAbbr")) %>%
    select(GeoName, state, total_stores, GDP_In_Millions_2024)

Walplot <- ggplot(merged_data, aes(x = total_stores, y = GDP_In_Millions_2024, label = state</pre>
```

#### 7.5 A correlation test

```
library(readxl)
library(dplyr)
gdp_data <- read_excel("desktop/state_statistics.xlsx") %>%
  select(state = StateAbbr, gdp = GDP_In_Millions_2024)
store_data <- read_excel("desktop/walmart_store_distribution.xlsx") %>%
  select(state, stores = total_stores)
combined_data <- inner_join(gdp_data, store_data, by = "state") %>%
  filter(!state %in% c("PR", "DC"))
pearson_test <- cor.test(combined_data$gdp, combined_data$stores,</pre>
                          method = "pearson")
spearman_test <- cor.test(combined_data$gdp, combined_data$stores,</pre>
                          method = "spearman")
cor_matrix <- cor(combined_data[, c("gdp", "stores")])</pre>
results <- list(
  pearson = list(
    estimate = pearson_test$estimate,
   p_value = pearson_test$p.value,
   conf_int = pearson_test$conf.int
  ),
  spearman = list(
```

```
estimate = spearman_test$estimate,
    p_value = spearman_test$p.value
),
    correlation_matrix = cor_matrix
)
```