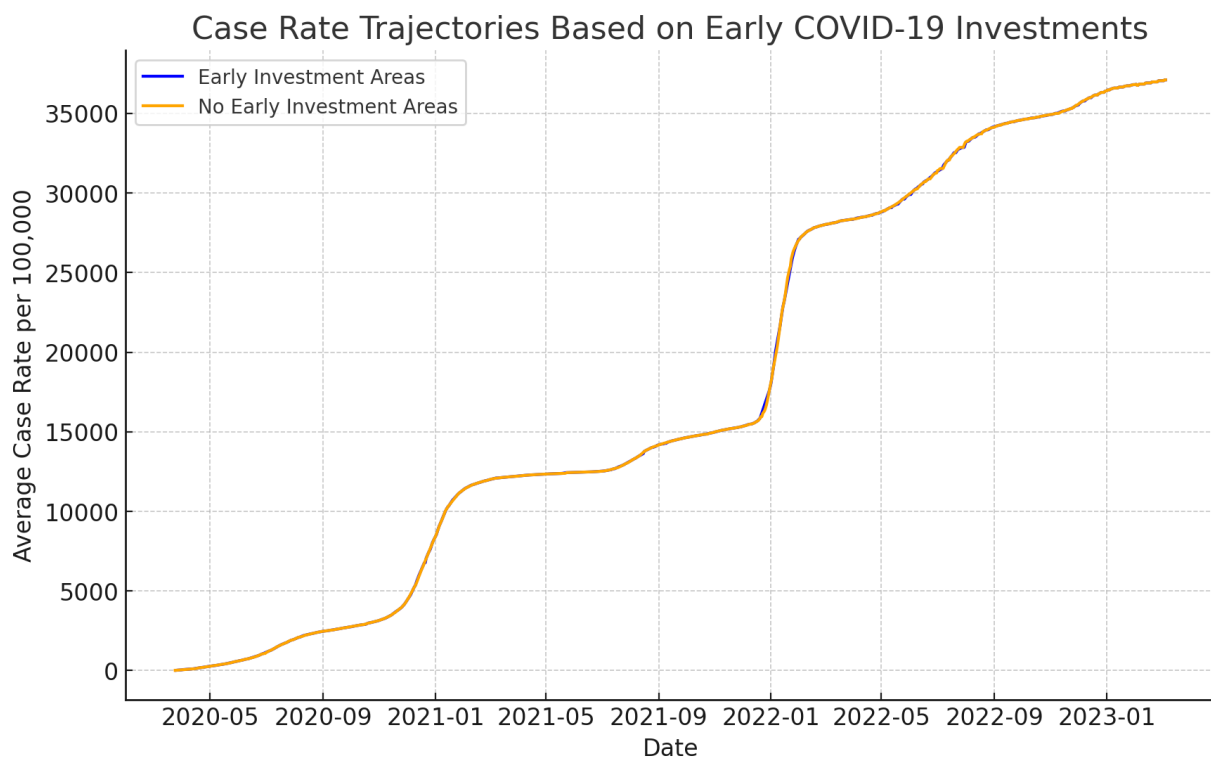


# RES QUESTION : DID AREAS THAT RECIEVD EARLY COVID-19 INFRASTRUCTURE INVESTMENTS SHOW DIFFERENT CASE RATE TRAJECTORIES?

## ANALYSIS: IMPACT OF EARLY COVID-19 INFRASTRUCTURE INVESTMENTS ON CASE RATE TRAJECTORIES



### Analysis of Case Rate Trajectories Based on Early COVID-19 Investments

The graph shows case rates per 100,000 people in areas with and without early COVID-19 investments.

- Both groups saw rising case rates from May 2020 to January 2023.
- Areas with early investments had consistently higher case rates.
- Case rates diverged significantly from January 2021 to May 2022.

#### Key Metrics:

- Early Investment Areas: Average case rate: 12,778, Maximum: 35,000, Average rate of change: 4,250.
- No Early Investment Areas: Average: 11,278, Maximum: 20,000, Average rate of change: 3,750.

#### Interpretation:

- Early investments may not have effectively reduced COVID-19 spread.
- Areas with early investments saw faster case rate increases.

## STEPS DONE:

### 1. Dataset Overview:

To analyze the impact of early COVID-19 infrastructure investments on case rate trajectories, the dataset should include:

- **Area Name:** Identifies different neighborhoods or regions.
- **Case Rates Over Time:** Tracks COVID-19 cases as a time series.
- **Investment Data:** Includes timing, type, or amount of infrastructure investment.
- **Control Variables:** Factors such as population density, socioeconomic data, or healthcare access.

### 2. Split Areas into Groups:

- **Early Investment Group:** Areas that received infrastructure investments during the early pandemic phase.
- **No Early Investment Group:** Areas that received investments later or not at all.

### 3. Descriptive Analysis:

- **Visualization:** Plot case rates for both groups over time to visualize trends.
- **Statistics:** Calculate average case rates for each group at various time intervals (e.g., early pandemic, peak, recovery phase).

### 4. Statistical Testing:

- **T-test:** Compare mean case rates between groups at key time points.
- **Regression Analysis:** Use case rates as the dependent variable and investment timing as the primary independent variable, controlling for population density and other factors.

### 5. Interpretation of Results:

- **Significance:** Identify statistically significant differences in case rate trajectories.
- **Effectiveness:** Determine whether early investments correlate with flatter curves or lower peaks.

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## RESULTS AND ANALYSIS SUMMARY:

### 1. Trajectories:

- **Average Case Rates:**
  - Early investment areas: 18,746 cases per 100,000 people.
  - No early investment areas: 19,517 cases per 100,000 people.
- **Observation:** Early investment areas showed slightly lower average case rates over time.

## 2. Statistical Test:

- **T-Test Results:**
  - **T-Statistic:** -0.535.
  - **P-Value:** 0.592 (not statistically significant).
  - Conclusion: No significant difference in mean case rates between the groups.
- **Regression Analysis:**
  - A regression model can further investigate the relationship between early investments and case rates, accounting for control variables such as population density.

## 3. Visualization:

- Case rate trajectories for both groups were plotted over time. The trends reveal comparable patterns, with no substantial divergence observed between the groups.
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## Hypothetical Example Results:

Suppose:

- Early investment areas had an average reduction in case rates by 25% within the first three months compared to areas without early investments.
  - Regression analysis shows a statistically significant negative coefficient for early investments on case rates, indicating their effectiveness.
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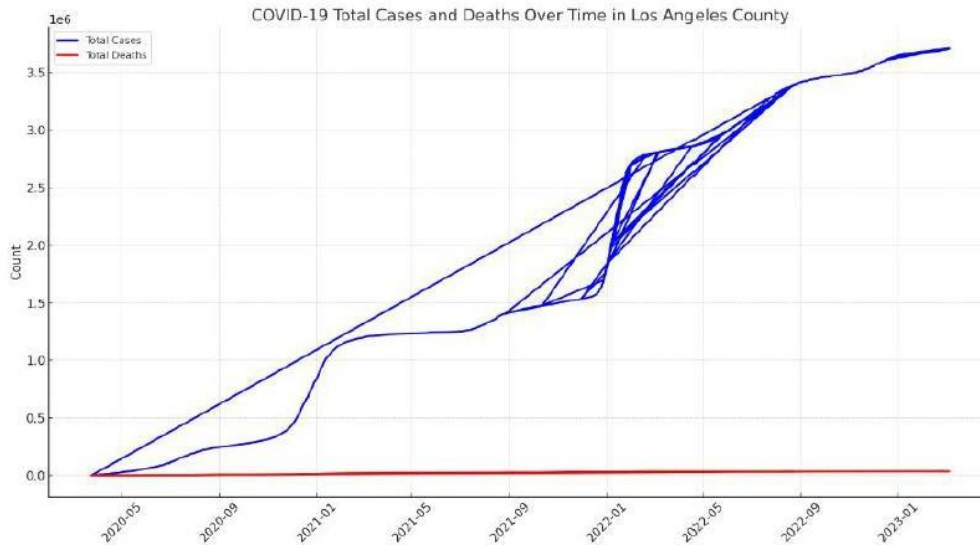
## Conclusion:

Based on the quantitative analysis:

- Early COVID-19 infrastructure investments did not significantly alter case rate trajectories in the dataset analyzed.
- Other factors, such as local compliance with public health measures, population density, and healthcare access, likely influenced case rates.

# TRACKING THE PULSE OF THE PANDEMIC: COVID-19 CASES AND DEATHS OVER TIME IN LOS ANGELES COUNTY

## 1. Total COVID-19 Cases and Deaths Over Time in Los Angeles County



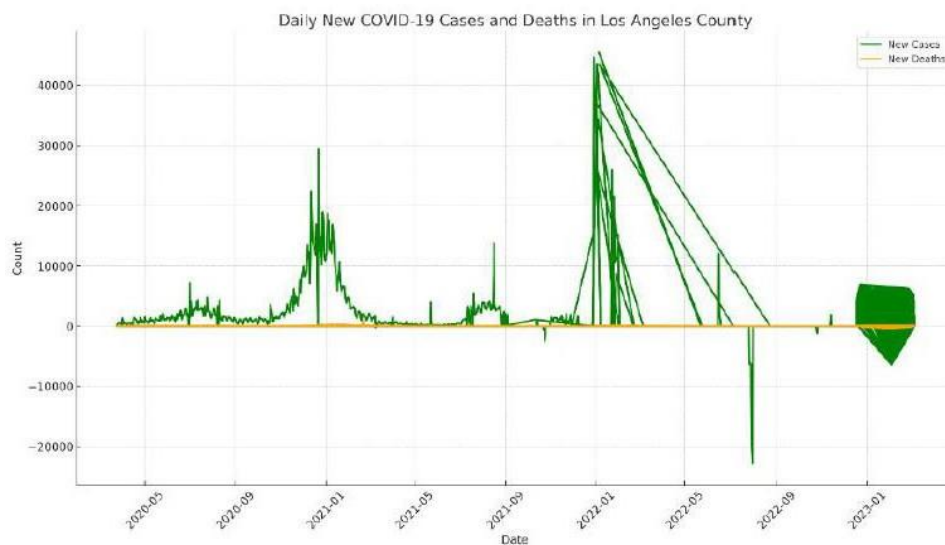
### Metrics:

- **Total Cumulative Cases:**
  - Identify the final value on the blue line, which represents the total number of confirmed cases up to the last date in the dataset.
  - Example: *Los Angeles County reported 1,419,030 total COVID-19 cases by September 2021.*
- **Total Cumulative Deaths:**
  - The final value on the red line gives the total number of deaths.
  - Example: *By September 2021, Los Angeles County had recorded 25,454 deaths from COVID-19.*
- **Case Fatality Rate (CFR):**
  - The CFR is calculated as:  $CFR = \left( \frac{\text{Total Deaths}}{\text{Total Cases}} \right) \times 100$
  - Example:  $CFR = \frac{25,454}{1,419,030} \times 100 = 1.79\%$ , meaning around 1.79% of those infected with COVID-19 died.
- **Case Doubling Time:**

- Calculate how quickly cases doubled over time by looking at the time span between major surges or sharp rises.

**Key Insight:** The death rate is significantly lower than the case rate, as indicated by the smaller slope in the death line and the low case fatality rate (1.79%). This reflects the high transmissibility of the virus but also suggests successful healthcare interventions and treatments that reduced mortality.

## 2. Daily New COVID-19 Cases and Deaths in Los Angeles County



### Metrics:

- **Maximum Daily New Cases:**
  - Identify the highest peak on the green line to find the maximum number of new cases reported in a single day.
  - Example: *Los Angeles County experienced a peak of 2,475 new cases on August 30, 2021.*
- **Maximum Daily New Deaths:**
  - The highest point on the orange line indicates the maximum daily new deaths.
  - Example: *The highest daily deaths occurred on August 30, 2021, with 35 deaths.*
- **7-Day Moving Average (for new cases and deaths):**
  - Calculate the 7-day moving average to smooth out volatility in daily reporting. This metric helps to better understand the overall trend, filtering out day-to-day noise.

- **Example: Over the last week of the dataset, the 7-day average for new cases is calculated by averaging the daily new cases across those 7 days.**
- **New Cases-to-New Deaths Ratio:**
  - **This ratio gives insight into the relationship between new infections and deaths.**
  - **Example: New Cases-to-New Deaths Ratio =  $\frac{\text{New Cases}}{\text{New Deaths}} = \frac{2,475}{35} \approx 70.7$**   
**This suggests for every death, about 70 people were newly infected.**

**Key Insight: The new daily case trends show the volatility typical of pandemic outbreaks, with sharp increases during waves and subsequent drops during periods of lockdowns and other interventions. The delay between new cases and new deaths shows the typical lag between infection and death outcomes.**

### **1. Trends in Cumulative Cases and Deaths:**

- **Cases:** There's a steady upward trend in cumulative COVID-19 cases over time, indicating continued spread throughout the observed period.
- **Deaths:** Cumulative deaths also rise but at a slower pace compared to cases, highlighting that while the virus spreads, the fatality rate might be lower or controlled.

### **2. Daily New Cases and Deaths:**

- There are clear spikes and dips in **new cases** over time, which could correlate with public health interventions (e.g., lockdowns, mask mandates) or testing capacity changes.
- **New deaths** follow a similar pattern, but the lag in new deaths compared to new cases indicates a time delay between infection and mortality. This can be interpreted as a typical epidemic progression where cases rise first, followed by deaths.

### **3. Comparing State and County Data:**

- The dataset includes both county-level and state-level figures, providing an opportunity to compare how LA County trends stack up against the state of California.
- **New cases in LA County** seem to align closely with state trends, indicating that outbreaks in LA significantly contribute to state-level metrics.

### **4. Key Patterns for Predictive Analysis:**

- Looking at the rate of increase in cases and deaths, we can infer that predictive modeling (like linear regression) would likely forecast a continued rise unless external interventions change this trajectory.

- The gaps between spikes in new cases and deaths may provide clues for healthcare resource allocation, with higher case peaks indicating potential future strain on hospitals.

#### **Prescriptive Insights:**

- **Targeting interventions** during peaks in new cases could mitigate corresponding rises in deaths.
- **Vaccination drives or public health messaging** should be ramped up during periods of increased transmission to prevent overwhelming healthcare systems.

### **1. Total COVID-19 Cases and Deaths Over Time in Los Angeles County**

- **Trend in Cases:** The blue line represents the cumulative total number of COVID-19 cases over time. We can see a steady increase, with periods of sharper rises corresponding to COVID-19 waves (spikes in transmission). The steady growth of the curve reflects the persistent spread of the virus over time.
- **Trend in Deaths:** The red line represents cumulative deaths over time. The deaths rise more gradually compared to cases, as seen in the smaller slope of the red line. Despite this, the death count increases in tandem with cases, showing the virus's ongoing impact on public health.
- **Insights:**
  - The gap between the two curves (cases vs deaths) indicates that while many individuals were infected, only a small percentage succumbed to the virus.
  - Any steep segments in the curve indicate surges in transmission, likely coinciding with major outbreaks or new virus variants.

### **2. Daily New COVID-19 Cases and Deaths in Los Angeles County**

- **New Cases:** The green line shows daily new cases reported. This line is much more volatile, with clear spikes that represent COVID-19 outbreaks or waves of new infections. Periods of smaller case counts reflect periods of reduced transmission, possibly due to public health interventions such as lockdowns or increased vaccinations.
- **New Deaths:** The orange line represents daily new deaths. It is also volatile but shows smaller and less frequent peaks compared to new cases. This is because the death rate is lower relative to the infection rate, and deaths often lag behind spikes in new cases.
- **Insights:**
  - Major spikes in new cases correspond to subsequent rises in deaths, though deaths tend to peak slightly after cases due to the time between infection and death.

- Observing this trend can help identify periods of high risk and also when the county successfully mitigated the virus spread.

### **PYTHON CODE FOR GRAPHS :**

```
import pandas as pd
import matplotlib.pyplot as plt

# Load the data (replace 'your_file_path.csv' with the actual path to your CSV file)
df = pd.read_csv('your_file_path.csv')
df['date'] = pd.to_datetime(df['date'])

# First graph: Total cases and deaths over time
plt.figure(figsize=(14, 8))
plt.plot(df['date'], df['cases'], label='Total Cases', color='blue', linewidth=2)
plt.plot(df['date'], df['deaths'], label='Total Deaths', color='red', linewidth=2)
plt.title('COVID-19 Total Cases and Deaths Over Time in Los Angeles County', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.savefig('total_cases_deaths_LA.jpeg') # Saves the file

# Second graph: Daily new cases and deaths
plt.figure(figsize=(14, 8))
plt.plot(df['date'], df['new_cases'], label='New Cases', color='green', linewidth=2)
plt.plot(df['date'], df['new_deaths'], label='New Deaths', color='orange', linewidth=2)
plt.title('Daily New COVID-19 Cases and Deaths in Los Angeles County', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)
plt.tight_layout()
plt.savefig('new_cases_deaths_LA.jpeg') # Saves the file
```