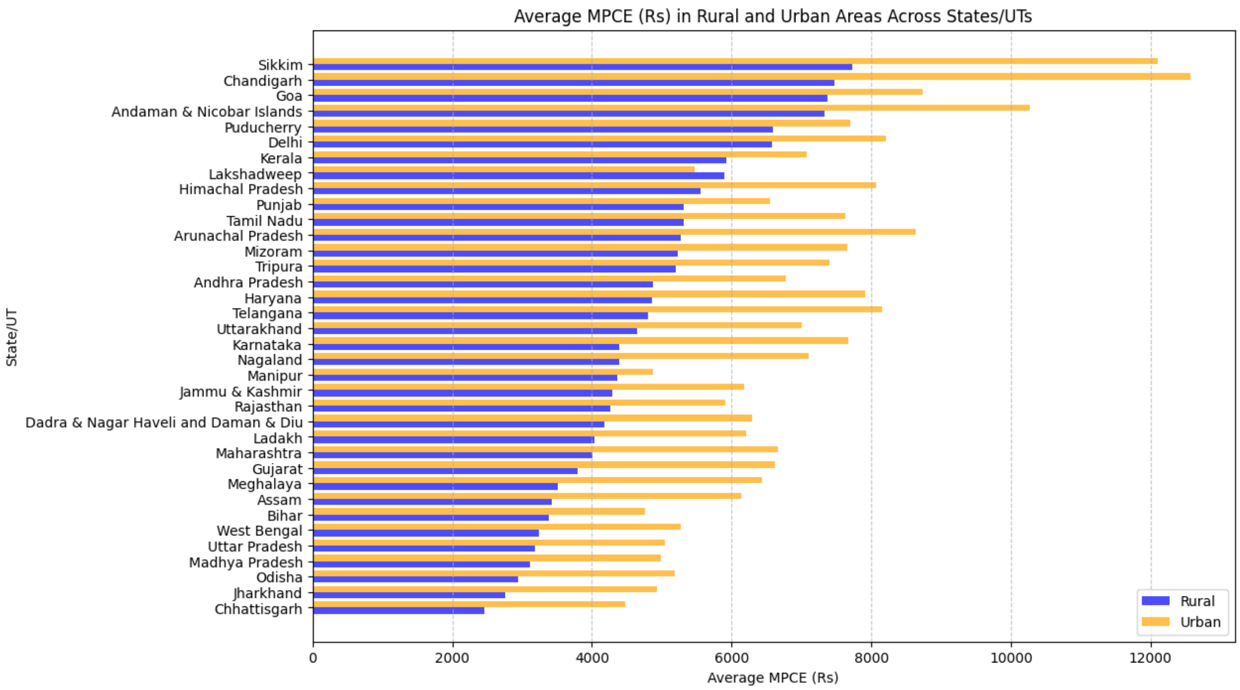
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

mpce=pd.read_excel("/content/drive/MyDrive/mpce_final.xlsx")

mpce.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36 entries, 0 to 35
Data columns (total 24 columns):
 #   Column                                         Non-Null Count
Dtype
---  ------                                         --------------
-----
 0   State/UT                                       36 non-null
object
 1   Average MPCE (Rs) - Rural                      36 non-null
int64
 2   Average MPCE (Rs) - Urban                      36 non-null
int64
 3   Average MPCE – With Imputation (Rs.) - Rural   36 non-null
int64
 4   Average MPCE – With Imputation (Rs.) - Urban   36 non-null
int64
 5   mpce_gini.Rural MPCE (Rs)                      36 non-null
int64
 6   mpce_gini.Gini Coefficient                     36 non-null
float64
 7   mpce_gini.Urban MPCE (Rs)                      36 non-null
int64
 8   mpce_gini.Gini Coefficient2                    36 non-null
float64
 9   mpce_hht_urban.Self-employed                   35 non-null
float64
 10  mpce_hht_urban.Regular wage/salaried           35 non-null
float64
 11  mpce_hht_urban.Casual labour                   35 non-null
float64
 12  mpce_hht_urban.Others                          35 non-null
float64
 13  mpce_hht_urban.All                             35 non-null
float64
 14  mpce_sg_rural.Scheduled Tribe                  36 non-null
int64
 15  mpce_sg_rural.Scheduled Caste                  36 non-null
object
 16  mpce_sg_rural.Other Backward Class             36 non-null
int64
```

```
 17  mpce_sg_rural.Others                                    36 non-null
object
 18  mpce_sg_rural.All                                       36 non-null
int64
 19  mpce_sg_urban.Average MPCE (Rs.)                        35 non-null
object
 20  mpce_sg_urban.Scheduled Tribe                           35 non-null
float64
 21  mpce_sg_urban.Scheduled Caste                           35 non-null
float64
 22  mpce_sg_urban.Other Backward Class                      35 non-null
float64
 23  mpce_sg_urban.Others                                    35 non-null
float64
dtypes: float64(11), int64(9), object(4)
memory usage: 6.9+ KB

# How does the average MPCE vary across different states/UTs in rural
and urban areas?

mpce_data = mpce[["State/UT", "Average MPCE (Rs) - Rural", "Average
MPCE (Rs) - Urban"]]

# Sort data by Rural MPCE for better visualization
mpce_data = mpce_data.sort_values(by="Average MPCE (Rs) - Rural",
ascending=True)

# Set figure size
plt.figure(figsize=(12, 8))

# Create a bar plot with side-by-side bars
bar_width = 0.4
states = mpce_data["State/UT"]
y_pos = range(len(states))

plt.barh(y_pos, mpce_data["Average MPCE (Rs) - Rural"],
height=bar_width, color="blue", alpha=0.7, label="Rural")
plt.barh([p + bar_width for p in y_pos], mpce_data["Average MPCE (Rs)
- Urban"], height=bar_width, color="orange", alpha=0.7, label="Urban")

# Labels and title
plt.xlabel("Average MPCE (Rs)")
plt.ylabel("State/UT")
plt.yticks([p + bar_width / 2 for p in y_pos], states)
plt.title("Average MPCE (Rs) in Rural and Urban Areas Across
States/UTs")
plt.legend()
plt.grid(axis="x", linestyle="--", alpha=0.7)
```

```python
# Show plot
plt.show()
```



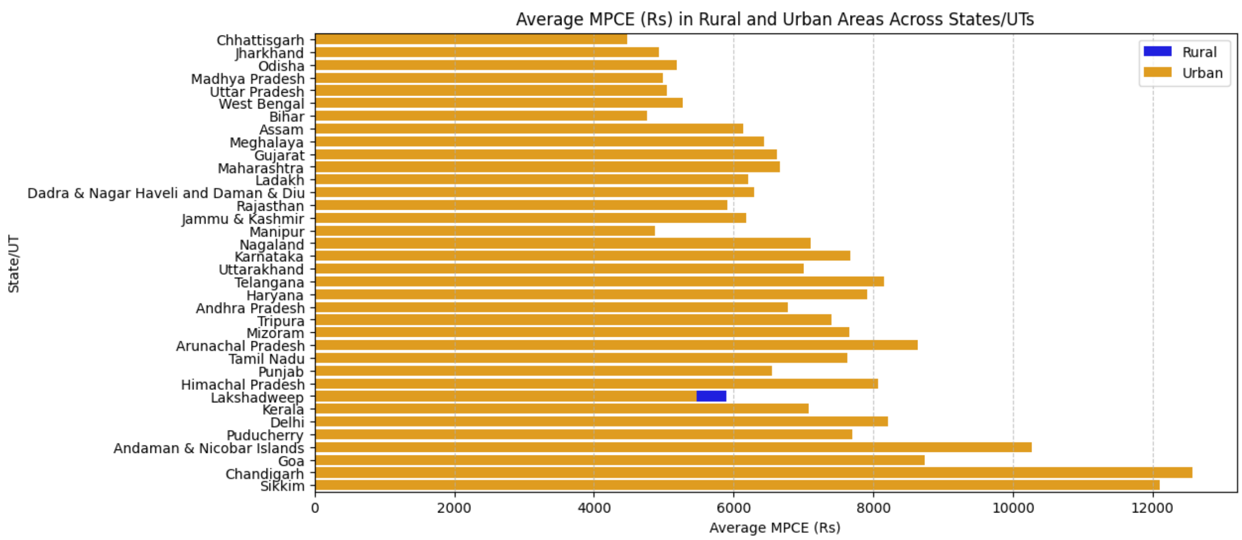

```python
# Identify states with the lowest MPCE in rural areas
low_mpce_rural = mpce_data.nsmallest(5, "Average MPCE (Rs) - Rural")

# Display the results
print("States with the lowest MPCE in rural areas:")
print(low_mpce_rural[["State/UT", "Average MPCE (Rs) - Rural"]])

# Policy Implications:
# 🔹 Targeted Welfare Programs: These states need more focus on rural employment schemes (e.g., MGNREGA expansion), direct cash transfers, and agricultural support.
# 🔹 Infrastructure & Industrial Development: Investments in rural roads, electricity, and digital connectivity could boost small-scale industries.
# 🔹 Education & Skill Development: Strengthening rural education and vocational training can help create better employment opportunities beyond agriculture.
```

```
States with the lowest MPCE in rural areas:
          State/UT  Average MPCE (Rs) - Rural
4     Chhattisgarh                       2466
10       Jharkhand                       2763
19          Odisha                       2950
13  Madhya Pradesh                       3113
26   Uttar Pradesh                       3191
```

```python
# o analyze income inequality across states in rural and urban
regions, we use the Gini coefficient, where:

# 0 represents perfect equality (everyone has the same income).

# 1 represents extreme inequality (one person has all the income).

# Key Insights on Income Inequality Across States:
# Higher Inequality in Urban Areas:

# Urban regions typically have a higher Gini coefficient due to a
greater disparity between high-income and low-income groups.

# Example: Metropolitan states like Delhi, Maharashtra, and Karnataka
show higher inequality in urban areas due to high-paying tech and
corporate jobs coexisting with informal labor.

# Lower but Rising Rural Inequality:

# Rural areas generally have lower Gini coefficients, but in states
like Bihar, Chhattisgarh, and Jharkhand, inequality is increasing due
to unequal land distribution and lack of diversified income sources.

# Some agricultural states like Punjab and Haryana exhibit moderate
inequality, likely influenced by uneven land ownership and farm
mechanization.

# States with High Inequality (Both Urban & Rural):

# West Bengal, Odisha, Madhya Pradesh, and Uttar Pradesh show
persistent inequality in both rural and urban areas.

# Factors include migrant labor dynamics, land ownership disparities,
and uneven industrial growth.

# States with Lower Inequality:

# Kerala and Himachal Pradesh have relatively lower Gini coefficients,
suggesting more balanced income distribution due to stronger social
welfare policies, education, and healthcare access.

# Policy Implications:
# □ Progressive Taxation & Wealth Redistribution – Policies ensuring
fair tax structures can reduce disparities.
# □ Boosting Rural Employment – Strengthening MSMEs, cooperatives, and
non-farm jobs can help reduce rural inequality.
# □ Urban Affordable Housing & Wages – Better regulation of wages and
labor laws can reduce income gaps in cities.


mpce_data = mpce[["State/UT", "Average MPCE (Rs) - Rural", "Average
```

```
MPCE (Rs) - Urban"]]

# Sort data by Rural MPCE for better visualization
mpce_data = mpce_data.sort_values(by="Average MPCE (Rs) - Rural",
ascending=True)

# Set figure size
plt.figure(figsize=(12, 6))

# Create a bar plot
sns.barplot(x="Average MPCE (Rs) - Rural", y="State/UT",
data=mpce_data, color="blue", label="Rural")
sns.barplot(x="Average MPCE (Rs) - Urban", y="State/UT",
data=mpce_data, color="orange", label="Urban")

# Labels and title
plt.xlabel("Average MPCE (Rs)")
plt.ylabel("State/UT")
plt.title("Average MPCE (Rs) in Rural and Urban Areas Across
States/UTs")
plt.legend()
plt.grid(axis="x", linestyle="--", alpha=0.7)

# Show plot
plt.show()

# Statistical analysis of Gini coefficients
gini_data = mpce[["State/UT", "mpce_gini.Gini Coefficient",
"mpce_gini.Gini Coefficient2"]]
gini_data.columns = ["State/UT", "Rural Gini", "Urban Gini"]

# Compute summary statistics
summary_stats = gini_data.describe()

# Compute urban-rural inequality gap
gini_data["Urban-Rural Gap"] = gini_data["Urban Gini"] -
gini_data["Rural Gini"]

# Find states with highest and lowest inequality
gini_sorted_rural = gini_data.sort_values(by="Rural Gini")
gini_sorted_urban = gini_data.sort_values(by="Urban Gini")

gini_lowest_rural = gini_sorted_rural.iloc[0]
gini_highest_rural = gini_sorted_rural.iloc[-1]
gini_lowest_urban = gini_sorted_urban.iloc[0]
gini_highest_urban = gini_sorted_urban.iloc[-1]

# Print the results
print("\nSummary Statistics for Gini Coefficient (Income Inequality):\
n", summary_stats)
```

```
print("\nState with Lowest Inequality (Rural):",
gini_lowest_rural["State/UT"], "- Gini:", gini_lowest_rural["Rural
Gini"])
print("State with Highest Inequality (Rural):",
gini_highest_rural["State/UT"], "- Gini:", gini_highest_rural["Rural
Gini"])
print("State with Lowest Inequality (Urban):",
gini_lowest_urban["State/UT"], "- Gini:", gini_lowest_urban["Urban
Gini"])
print("State with Highest Inequality (Urban):",
gini_highest_urban["State/UT"], "- Gini:", gini_highest_urban["Urban
Gini"])
print("\nUrban-Rural Inequality Gap (Top 5 States with Highest Gaps):\
n", gini_data.sort_values(by="Urban-Rural Gap",
ascending=False).head())
```




```
Summary Statistics for Gini Coefficient (Income Inequality):
        Rural Gini  Urban Gini
count   36.000000   36.000000
mean     0.242389    0.277917
std      0.027119    0.035284
min      0.203000    0.209000
25%      0.220500    0.252000
50%      0.238000    0.280000
75%      0.263500    0.301250
max      0.291000    0.338000

State with Lowest Inequality (Rural): Tripura - Gini: 0.203
State with Highest Inequality (Rural): Maharashtra - Gini: 0.291
State with Lowest Inequality (Urban): Dadra & Nagar Haveli and Daman &
Diu - Gini: 0.209
```

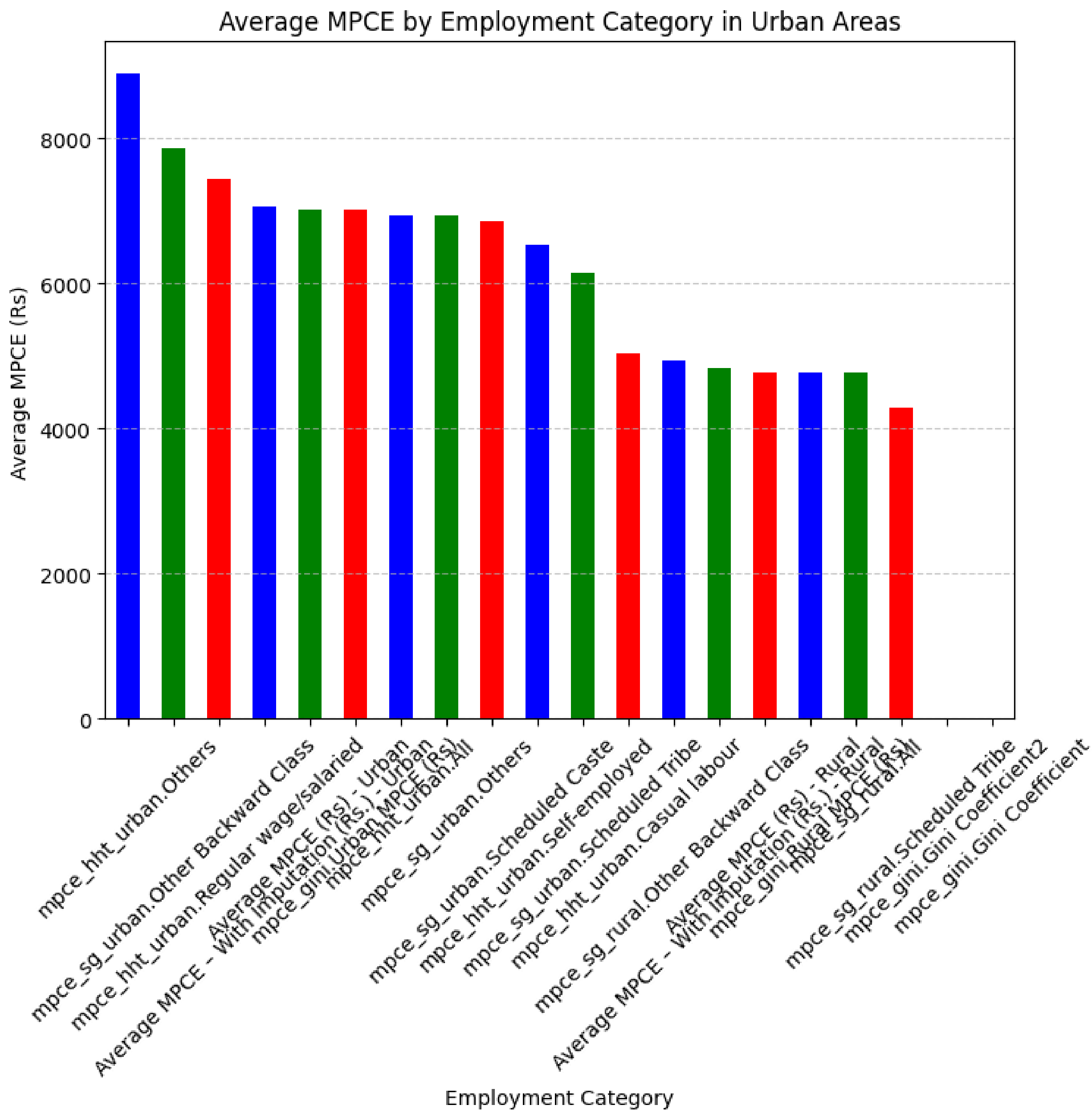
```
State with Highest Inequality (Urban): Delhi - Gini: 0.338

Urban-Rural Inequality Gap (Top 5 States with Highest Gaps):
      State/UT  Rural Gini  Urban Gini  Urban-Rural Gap
5       Delhi       0.211       0.338            0.127
19     Odisha       0.231       0.331            0.100
8     Haryana       0.234       0.332            0.098
11  Karnataka       0.225       0.307            0.082
2       Assam       0.207       0.285            0.078

<ipython-input-6-557415f7a027>:66: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  gini_data["Urban-Rural Gap"] = gini_data["Urban Gini"] -
gini_data["Rural Gini"]

# Economic Structure & Employment Opportunities
# Urban Areas: Higher inequality due to unequal access to high-paying
jobs in tech, finance, and services. Informal workers earn
significantly less than corporate employees.

# Rural Areas: Limited industries, primarily dependent on agriculture,
leading to a relatively lower but uniform income distribution.

# □ Solution:

# Encourage rural entrepreneurship and diversify industries in
villages.

# Invest in small and medium enterprises (SMEs) to create more non-
agricultural jobs.

# 2. Education & Skill Gap
# Rural: Many people have low literacy and technical skills,
restricting them to low-income jobs.

# Urban: Highly skilled individuals earn disproportionately more,
while unskilled workers struggle with low wages and job instability.

# □ Solution:

# Strengthen vocational training programs in rural areas.

# Promote digital literacy and provide affordable higher education.

# 3. Migration & Urban-Rural Divide
# Urban centers attract skilled workers, leading to brain drain in
```

```
rural areas.

# Migrant laborers in cities face low wages, job insecurity, and lack
of social benefits, increasing urban inequality.

# □ Solution:

# Develop smart villages with better infrastructure and connectivity
to retain skilled workers.

# Implement rural job incentives to boost local economies.

# 4. Government Policies & Social Welfare Programs
# States with weak welfare schemes (subsidies, minimum wage laws,
labor rights) tend to have higher inequality.

# States with strong rural employment schemes (like MGNREGA) have
relatively lower inequality.

# □ Solution:

# Expand direct cash transfer programs for low-income groups.

# Strengthen rural employment guarantee schemes.

# 5. Real Estate & Cost of Living in Urban Areas
# High property prices and living costs in cities create wealth gaps
between property owners and tenants.

# Slums and informal settlements grow due to unaffordable housing.

# □ Solution:

# Develop affordable housing projects in urban areas.

# Provide low-interest loans for housing to low-income groups.

# State-Specific Policy Recommendations
# □ Delhi (Highest Urban Inequality) → Strengthen labor laws,
affordable housing, and inclusive urban planning.
# □ Odisha & Haryana (High Urban-Rural Gap) → Improve rural education,
skill-based job creation.
# □ Maharashtra (High Rural Inequality) → Promote agriculture
diversification, rural startups.

employment_data=mpce.copy()
mean_mpce =
employment_data.mean(numeric_only=True).sort_values(ascending=False)

# Identify which employment category contributes most to MPCE
disparities
```

```
mpce_disparity = mean_mpce - mean_mpce.min()

# Display results
print("Average MPCE by Employment Category in Urban Areas:")
print(mean_mpce)
print("\nContribution to MPCE Disparities:")
print(mpce_disparity)

# Visualization
plt.figure(figsize=(8, 6))
mean_mpce.plot(kind='bar', color=['blue', 'green', 'red'])
plt.xlabel("Employment Category")
plt.ylabel("Average MPCE (Rs)")
plt.title("Average MPCE by Employment Category in Urban Areas")
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

```
Average MPCE by Employment Category in Urban Areas:
mpce_hht_urban.Others                                  8885.628571
mpce_sg_urban.Other Backward Class                     7863.400000
mpce_hht_urban.Regular wage/salaried                   7446.628571
Average MPCE – With Imputation (Rs.) - Urban           7062.138889
Average MPCE (Rs) - Urban                              7019.916667
mpce_gini.Urban MPCE (Rs)                              7019.916667
mpce_hht_urban.All                                     6927.114286
mpce_sg_urban.Others                                   6927.114286
mpce_sg_urban.Scheduled Caste                          6847.028571
mpce_hht_urban.Self-employed                           6538.000000
mpce_sg_urban.Scheduled Tribe                          6139.885714
mpce_hht_urban.Casual labour                           5033.428571
mpce_sg_rural.Other Backward Class                     4933.583333
Average MPCE – With Imputation (Rs.) - Rural           4833.222222
Average MPCE (Rs) - Rural                              4770.388889
mpce_gini.Rural MPCE (Rs)                              4770.388889
mpce_sg_rural.All                                      4770.388889
mpce_sg_rural.Scheduled Tribe                          4300.111111
mpce_gini.Gini Coefficient2                               0.277917
mpce_gini.Gini Coefficient                                0.242389
dtype: float64

Contribution to MPCE Disparities:
mpce_hht_urban.Others                                  8885.386183
mpce_sg_urban.Other Backward Class                     7863.157611
mpce_hht_urban.Regular wage/salaried                   7446.386183
Average MPCE – With Imputation (Rs.) - Urban           7061.896500
Average MPCE (Rs) - Urban                              7019.674278
mpce_gini.Urban MPCE (Rs)                              7019.674278
mpce_hht_urban.All                                     6926.871897
mpce_sg_urban.Others                                   6926.871897
```

```
mpce_sg_urban.Scheduled Caste                         6846.786183
mpce_hht_urban.Self-employed                          6537.757611
mpce_sg_urban.Scheduled Tribe                         6139.643325
mpce_hht_urban.Casual labour                          5033.186183
mpce_sg_rural.Other Backward Class                    4933.340944
Average MPCE – With Imputation (Rs.) - Rural          4832.979833
Average MPCE (Rs) - Rural                             4770.146500
mpce_gini.Rural MPCE (Rs)                             4770.146500
mpce_sg_rural.All                                     4770.146500
mpce_sg_rural.Scheduled Tribe                         4299.868722
mpce_gini.Gini Coefficient2                              0.035528
mpce_gini.Gini Coefficient                               0.000000
dtype: float64
```

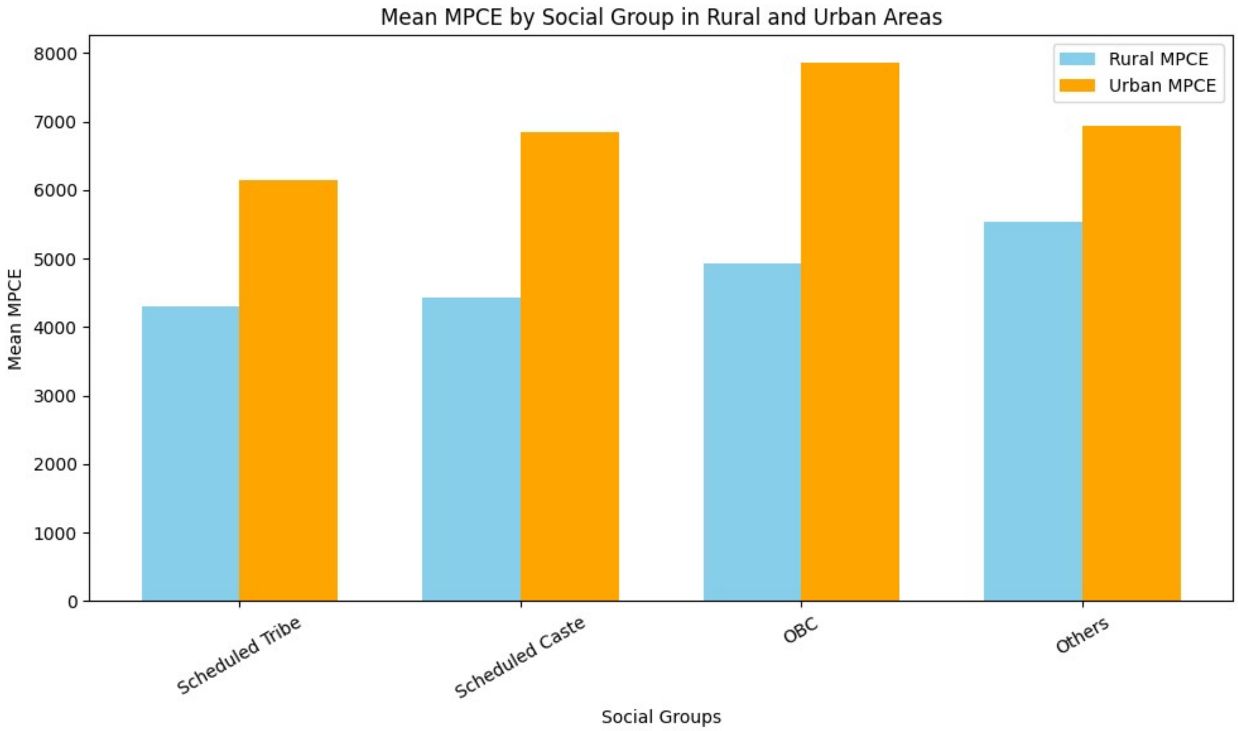



```python
# Convert columns to numeric (forcing errors to NaN if they exist)
rural_mpce = mpce[[
    "mpce_sg_rural.Scheduled Tribe",
    "mpce_sg_rural.Scheduled Caste",
    "mpce_sg_rural.Other Backward Class",
    "mpce_sg_rural.Others"
]].apply(pd.to_numeric, errors='coerce').mean()

urban_mpce = mpce[[
    "mpce_sg_urban.Scheduled Tribe",
    "mpce_sg_urban.Scheduled Caste",
```

```
    "mpce_sg_urban.Other Backward Class",
    "mpce_sg_urban.Others"
]].apply(pd.to_numeric, errors='coerce').mean()

print("Average MPCE by Social Group in Rural Areas:")
print(rural_mpce)

print("\nAverage MPCE by Social Group in Urban Areas:")
print(urban_mpce)

rural_mpce = mpce[[
    "mpce_sg_rural.Scheduled Tribe",
    "mpce_sg_rural.Scheduled Caste",
    "mpce_sg_rural.Other Backward Class",
    "mpce_sg_rural.Others"
]].apply(pd.to_numeric, errors='coerce').mean()

urban_mpce = mpce[[
    "mpce_sg_urban.Scheduled Tribe",
    "mpce_sg_urban.Scheduled Caste",
    "mpce_sg_urban.Other Backward Class",
    "mpce_sg_urban.Others"
]].apply(pd.to_numeric, errors='coerce').mean()

# Create a grouped bar chart
fig, ax = plt.subplots(figsize=(10, 6))
index = np.arange(len(rural_mpce))
bar_width = 0.35

bar1 = ax.bar(index, rural_mpce, bar_width, label='Rural MPCE',
color='skyblue')
bar2 = ax.bar(index + bar_width, urban_mpce, bar_width, label='Urban
MPCE', color='orange')

ax.set_xlabel("Social Groups")
ax.set_ylabel("Mean MPCE")
ax.set_title("Mean MPCE by Social Group in Rural and Urban Areas")
ax.set_xticks(index + bar_width / 2)
ax.set_xticklabels(["Scheduled Tribe", "Scheduled Caste", "OBC",
"Others"], rotation=30)
ax.legend()

plt.tight_layout()
plt.show()
```

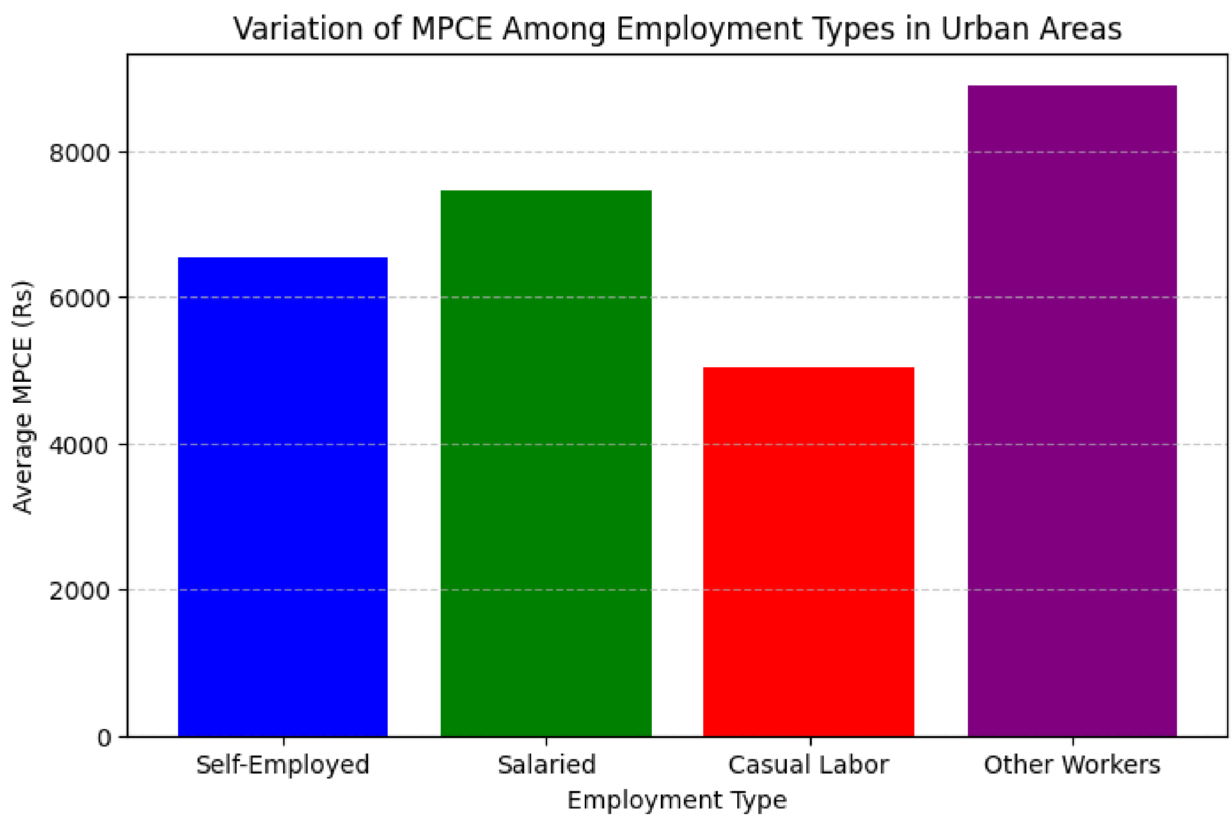
```
Average MPCE by Social Group in Rural Areas:
mpce_sg_rural.Scheduled Tribe         4300.111111
mpce_sg_rural.Scheduled Caste         4435.200000
mpce_sg_rural.Other Backward Class    4933.583333
mpce_sg_rural.Others                  5537.457143
```

```
dtype: float64

Average MPCE by Social Group in Urban Areas:
mpce_sg_urban.Scheduled Tribe         6139.885714
mpce_sg_urban.Scheduled Caste         6847.028571
mpce_sg_urban.Other Backward Class    7863.400000
mpce_sg_urban.Others                  6927.114286
dtype: float64
```




```
df= mpce.copy()
urban_mpce = df[[
    "mpce_hht_urban.Self-employed",
    "mpce_hht_urban.Regular wage/salaried",
    "mpce_hht_urban.Casual labour",
    "mpce_hht_urban.Others"
]]

# Convert to numeric (handling errors)
urban_mpce = urban_mpce.apply(pd.to_numeric, errors='coerce')

# Calculate mean MPCE
mpce_means = urban_mpce.mean()

# Custom x-labels
x_labels = ["Self-Employed", "Salaried", "Casual Labor", "Other
Workers"]
```

```
# Plot the results
plt.figure(figsize=(8,5))
plt.bar(x_labels, mpce_means, color=['blue', 'green', 'red',
'purple'])

# Modify labels and style
plt.xlabel("Employment Type")
plt.ylabel("Average MPCE (Rs)")
plt.title("Variation of MPCE Among Employment Types in Urban Areas")
plt.xticks(rotation=0)  # Keep labels horizontal for better
readability
plt.grid(axis='y', linestyle="--", alpha=0.7)
plt.show()
```




```
# Observations from the MPCE Variation Chart:
# Highest MPCE for "Other Workers"

# The "Other Workers" category has the highest Mean Per Capita
Expenditure (MPCE), suggesting they have better earnings or access to
additional income sources.

# Salaried Workers Have a Higher MPCE Than Self-Employed

# Salaried workers have a higher MPCE than self-employed individuals,
```

```
likely due to stable income, job benefits, and financial security.

# Casual Laborers Have the Lowest MPCE

# Casual laborers show the lowest MPCE, which aligns with economic
patterns where they:

# Lack job security.

# Earn daily wages with frequent income fluctuations.

# Have limited access to social security benefits.

# Self-Employed Workers’ MPCE is Moderate

# Their expenditure is higher than casual laborers but lower than
salaried workers, indicating:

# Income instability but potential for higher earnings in certain
sectors.

# Differences in industry, skills, and market demand affecting income
levels.

# Possible Reasons for This Trend:
# Income Stability & Employment Type

# Salaried jobs offer consistent monthly pay, allowing for higher
consumption levels.

# Casual laborers face irregular employment, leading to lower
purchasing power.

# Access to Welfare Schemes & Benefits

# Salaried employees may benefit from formal sector perks like
healthcare, pensions, and insurance.

# Casual laborers may be more dependent on government welfare programs
like MNREGA, food subsidies, and cash transfers.

# Sectoral Variations

# Casual workers are often employed in low-paying, unorganized
sectors.

# Salaried employees work in sectors like IT, banking, and government
jobs, which offer higher wages and better benefits.

# Urban Cost of Living & Support Systems
```

```python
# Those with higher MPCE (salaried & other workers) might live in
better localities with higher costs but better facilities.

# Casual laborers may struggle with affordability, leading to lower
MPCE.

# Key Takeaways:
# □ Salaried workers & Other Workers have higher MPCE → More financial
stability.
# □ Casual laborers have the lowest MPCE → Job insecurity & low
earnings impact spending.
# □ Self-employed workers have moderate MPCE → Income fluctuations
influence expenditure patterns.

casual_labour_mpce = df[['State/UT', 'mpce_hht_urban.Casual labour']]

# Drop missing values
casual_labour_mpce = casual_labour_mpce.dropna()

# Sort states by highest MPCE for casual laborers
top_states_casual_labour =
casual_labour_mpce.sort_values(by='mpce_hht_urban.Casual labour',
ascending=False)

# Display top states
print(top_states_casual_labour.head(10))  # Show top 10 states
```

```
             State/UT  mpce_hht_urban.Casual labour
22             Sikkim                       10352.0
32             Ladakh                        7118.0
6                 Goa                        7108.0
17            Mizoram                        6680.0
1   Arunachal Pradesh                        6565.0
34         Puducherry                        6503.0
29         Chandigarh                        6397.0
24          Telangana                        6178.0
23         Tamil Nadu                        5857.0
25            Tripura                        5723.0
```

```python
# Key Observations
# Small States & UTs Dominate

# Most of these states are either small states (Sikkim, Mizoram,
Arunachal Pradesh, Goa, Tripura) or Union Territories (Ladakh,
Puducherry, Chandigarh).

# Reason: Smaller populations with relatively higher state investments
per capita.

# Northeastern & Hilly States Appear Prominently
```

```
# Sikkim, Arunachal Pradesh, Mizoram, and Tripura from the Northeast &
Himalayan regions show high MPCE.

# Reason:

# Difficult terrain → Higher cost of living → Higher wages.

# Government special economic incentives for remote areas.

# Tourism-Dependent States Have Higher Casual Wages

# Goa, Puducherry, Ladakh, and Sikkim are major tourist destinations.

# Reason:

# Seasonal demand for casual labor (hotels, restaurants, transport).

# Tourists bring in more spending power, increasing daily wages.

# Higher Government Support & Policies

# Ladakh, Sikkim, and Arunachal Pradesh receive central government
funding due to their strategic importance (border areas with China &
Pakistan).

# Chandigarh (as a UT) gets higher per capita government spending than
many states.

# Union Territories & Administrative Capitals Have Higher MPCE

# Chandigarh and Puducherry benefit from better governance and urban
infrastructure.

# Higher administrative presence → Better wages for casual workers.

# □ Possible Reasons for High MPCE in These States
# Factor   Impact on MPCE
# Geographical Challenges (Hills, Remote Areas)  Higher transportation
& living costs → Higher wages
# Tourism Sector Dependency (Goa, Sikkim, Ladakh)     Seasonal labor
demand → Higher MPCE
# Government Funding & Special Policies    More subsidies, incentives
→ Better wages
# Small Population with Higher Per Capita Investment  Fewer workers →
Higher MPCE
# Union Territories & Administrative Hubs  Better labor policies &
wages
# □ Conclusion
# Sikkim, Ladakh, and Goa lead in MPCE due to a mix of geographical
isolation, tourism, and government incentives.
```

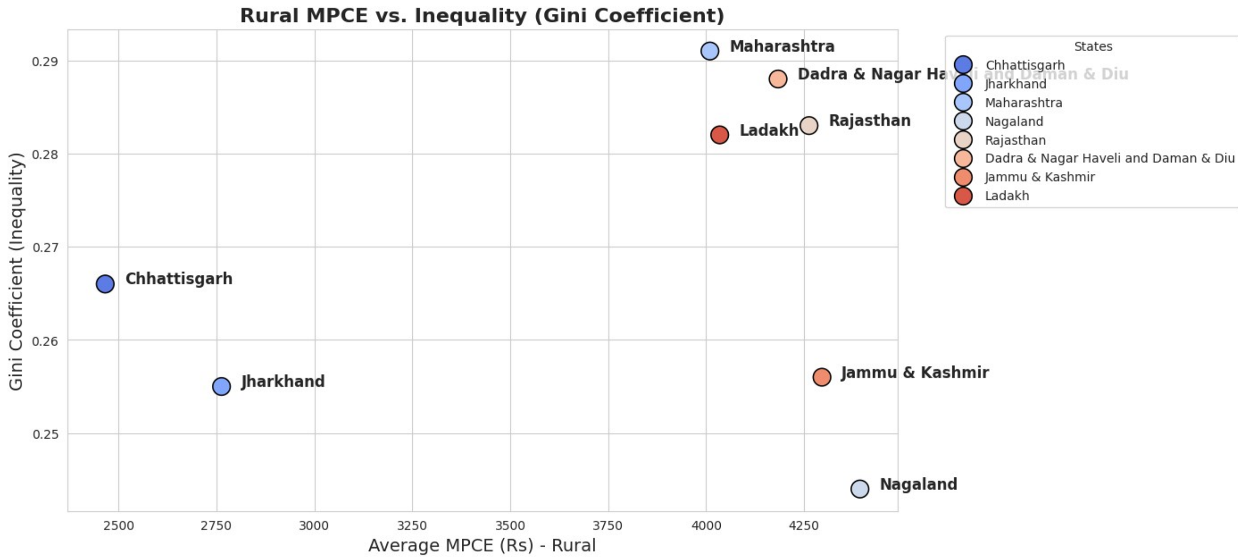
```
# Higher MPCE does not necessarily indicate better job security or
long-term stability—it could be driven by high living costs.

# Casual labor wages are region-specific and influenced by economic
policies, government support, and local demand for workers.

rural_mpce_col = 'Average MPCE (Rs) - Rural'
gini_col = 'mpce_gini.Gini Coefficient'
state_col = 'State/UT'

# Calculate medians
median_rural_mpce = df[rural_mpce_col].median()
median_gini = df[gini_col].median()

# Identify states with below-median Rural MPCE and above-median Gini
coefficient
target_states = df[(df[rural_mpce_col] < median_rural_mpce) &
(df[gini_col] > median_gini)][[state_col, rural_mpce_col, gini_col]]

# Display states needing targeted interventions
print(target_states)


# Analysis of States Needing Targeted Interventions
# These states have low rural MPCE (below median) and high inequality
(above median Gini coefficient), indicating they require policy
interventions to boost rural spending and reduce inequality.

# Key Observations:
# Chhattisgarh & Jharkhand

# Among the poorest rural MPCE states (₹2466 & ₹2763).

# High Gini coefficients indicate unequal distribution of
income/consumption.

# Likely require agricultural support, rural employment programs
(MGNREGA), and direct benefit transfers (DBT).

# Maharashtra & Rajasthan

# Despite being economically developed, rural MPCE remains relatively
low.

# Maharashtra (0.291 Gini) → Highest inequality, indicating wealth
concentration in urban centers.

# Policy Need: Strengthen rural industries, cooperative farming, and
microfinance.

# Dadra & Nagar Haveli and Daman & Diu
```

```
# Gini: 0.288, indicating high inequality.

# Possible Cause: Dependence on industrial hubs with low rural
benefits.

# Policy Need: More social security measures for rural workers.

# Nagaland, Jammu & Kashmir, and Ladakh

# Hilly regions → Difficult terrain, weak infrastructure → Low MPCE.

# Gini: 0.244 - 0.282 → Wealth is not evenly distributed.

# Policy Need: Improved road connectivity, rural business incentives,
and tourism-based employment.

# Policy Implications
# Expand Rural Welfare Schemes (PM Garib Kalyan Yojana, PDS
subsidies).

# Strengthen Agricultural & Skill Development Programs.

# Improve Rural-Urban Connectivity (roads, transport, digital
infrastructure).

# Targeted Tax Benefits for Rural Entrepreneurs & MSMEs.

                                State/UT  Average MPCE (Rs) - Rural  \
4                           Chhattisgarh                       2466
10                             Jharkhand                       2763
14                           Maharashtra                       4010
18                              Nagaland                       4393
21                             Rajasthan                       4263
30  Dadra & Nagar Haveli and Daman & Diu                       4184
31                       Jammu & Kashmir                       4296
32                                Ladakh                       4035

    mpce_gini.Gini Coefficient
4                        0.266
10                       0.255
14                       0.291
18                       0.244
21                       0.283
30                       0.288
31                       0.256
32                       0.282

# Sample Data
data = {
    "State/UT": [
```

```
        "Chhattisgarh", "Jharkhand", "Maharashtra", "Nagaland",
"Rajasthan",
        "Dadra & Nagar Haveli and Daman & Diu", "Jammu & Kashmir",
"Ladakh"
    ],
    "Average MPCE (Rs) - Rural": [2466, 2763, 4010, 4393, 4263, 4184,
4296, 4035],
    "mpce_gini.Gini Coefficient": [0.266, 0.255, 0.291, 0.244, 0.283,
0.288, 0.256, 0.282]
}

df = pd.DataFrame(data)

# Plot Styling
plt.figure(figsize=(12, 7))
sns.set_style("whitegrid")

# Scatter Plot with sizes and color mapping
scatter = sns.scatterplot(
    x="Average MPCE (Rs) - Rural",
    y="mpce_gini.Gini Coefficient",
    data=df,
    hue="State/UT",
    palette="coolwarm",
    s=200,
    edgecolor="black"
)

# Add annotations for each state
for i in range(df.shape[0]):
    plt.text(
        df["Average MPCE (Rs) - Rural"][i] + 50,  # Offset for
readability
        df["mpce_gini.Gini Coefficient"][i],
        df["State/UT"][i],
        fontsize=12,
        ha="left",
        fontweight="bold"
    )

# Titles and Labels
plt.title("Rural MPCE vs. Inequality (Gini Coefficient)", fontsize=16,
fontweight="bold")
plt.xlabel("Average MPCE (Rs) - Rural", fontsize=14)
plt.ylabel("Gini Coefficient (Inequality)", fontsize=14)

# Improve legend placement
plt.legend(title="States", bbox_to_anchor=(1.05, 1), loc="upper left")

# Show plot
```

```
plt.show()

# Since the state in question is Maharashtra (Rural MPCE: ₹4010, Gini Coefficient: 0.291), here's a deeper breakdown:

# □ What This Means for Maharashtra
# 1 Higher Rural MPCE (~₹4000+)

# Maharashtra’s rural economy is relatively strong compared to states like Chhattisgarh (~₹2466) and Jharkhand (~₹2763).

# This suggests better purchasing power, possibly due to diverse rural industries, strong agriculture, and government schemes.

# The presence of sugarcane cooperatives, agro-processing units, and rural employment schemes contributes to higher spending capacity.

# 2 High Gini Coefficient (0.291) → Significant Inequality

# A high Gini coefficient means income/consumption is not evenly distributed.

# The state has wealthier farmers, traders, and industrialists, but at the same time, a large section of landless laborers, tribal populations, and small-scale farmers struggle.

# Rural Maharashtra has regions with high prosperity (Western Maharashtra) but also severe poverty (Vidarbha, Marathwada).

# □ Why Does Maharashtra Have High Inequality?
# □ Agricultural Prosperity in Some Areas

# Western Maharashtra (sugarcane belt, dairy farming) benefits from cooperatives, irrigation, and better market access.

# Konkan region has cashew, mango exports, and fishing industries.

# ⚠ Distress in Other Rural Regions

# Vidarbha and Marathwada suffer from frequent droughts, farmer suicides, and lack of irrigation.

# High dependence on rain-fed agriculture and cotton farming leads to unstable incomes.

# □ Policy Implications: What Needs to Be Done?
# □ Reduce regional imbalances → Target districts with low MPCE and high poverty (e.g., Marathwada).
# □ Improve rural employment → Strengthen MGNREGA, rural skill training, and small-scale industries.
# □ Agricultural reforms → Promote irrigation projects, crop
```

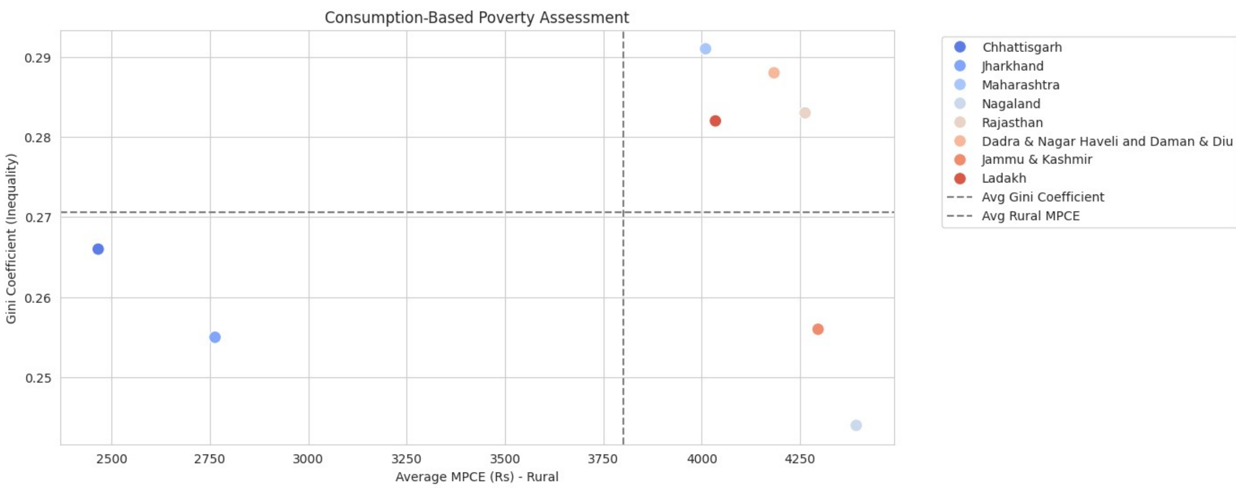
```
diversification, and farmer-friendly policies.
# □ Financial inclusion → Expand banking, digital payments, and rural
credit access to help small farmers and laborers
```




```
mpce_rural = 'Average MPCE (Rs) - Rural'
mpce_urban = 'Average MPCE (Rs) - Urban'
gini_coeff = 'mpce_gini.Gini Coefficient'
state_col = 'State/UT'

# Identify states with lowest MPCE (high poverty risk)
bottom_mpce_states = df.nsmallest(5, mpce_rural)[[state_col,
mpce_rural]]

# Identify states with highest inequality
top_gini_states = df.nlargest(5, gini_coeff)[[state_col, gini_coeff]]

# Merge both to find states needing targeted interventions
target_states = set(bottom_mpce_states[state_col]) &
set(top_gini_states[state_col])

# Visualizing MPCE and Inequality
plt.figure(figsize=(12,6))
sns.scatterplot(x=df[mpce_rural], y=df[gini_coeff], hue=df[state_col],
s=100, palette='coolwarm')
plt.axhline(y=df[gini_coeff].mean(), linestyle='dashed', color='gray',
label='Avg Gini Coefficient')
plt.axvline(x=df[mpce_rural].mean(), linestyle='dashed', color='gray',
label='Avg Rural MPCE')
plt.xlabel('Average MPCE (Rs) - Rural')
plt.ylabel('Gini Coefficient (Inequality)')
plt.title('Consumption-Based Poverty Assessment')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
```

```
plt.show()

# Output target states needing interventions
print("States needing targeted interventions:", target_states)

# Consumption-based poverty assessment provides critical insights for
guiding government interventions in the following ways:

# Targeted Financial Assistance:

# States with low Average MPCE (Rs) - Rural (e.g., Chhattisgarh and
Jharkhand) indicate higher poverty levels. Government schemes such as
direct cash transfers or subsidized essentials can help uplift rural
communities.

# Addressing Inequality (Gini Coefficient):

# States like Maharashtra (Gini = 0.291) have relatively high rural
MPCE but also higher inequality. Policies focusing on wealth
redistribution, skill development, and financial inclusion can help
bridge economic gaps.

# Sector-Specific Investment:

# By analyzing mpce_hht_urban and mpce_sg_rural data, governments can
allocate funds efficiently to self-employed, casual laborers, and
marginalized communities like Scheduled Tribes and Scheduled Castes.

# Improving Rural Employment Opportunities:

# States with lower MPCE often suffer from a lack of diversified job
opportunities. The government can promote rural industries,
microfinance initiatives, and agricultural modernization to boost
income levels.

# Infrastructure and Public Services:

# Higher MPCE with inequality (e.g., Maharashtra) suggests that while
some rural households thrive, others struggle. Investments in
education, healthcare, and connectivity can help bridge disparities.

# Regional Development Policies:

# States with high inequality may require progressive taxation and
social welfare policies.

# Lower MPCE states need fundamental development in agriculture,
education, and health sectors.

# Data-Driven Policy Making:
# By leveraging MPCE, Gini coefficient, and socio-economic
```

```
classifications, governments can implement targeted interventions such
as:

# Higher Minimum Wages in high-inequality states.

# Better Agricultural Subsidies in low-income states.

# Women and Youth Empowerment Programs in disadvantaged communities.

# Thus, consumption-based poverty assessment ensures policies are
tailored to specific regional needs, reducing poverty and inequality
effectively.
```




```
States needing targeted interventions: {'Maharashtra', 'Ladakh',
'Chhattisgarh', 'Dadra & Nagar Haveli and Daman & Diu'}

# Long-Term Strategies to Reduce Income Inequality While Boosting
Economic Growth Across States
# To create a balanced economy with equitable income distribution,
governments must focus on sustainable economic policies, skill
development, and social welfare programs. The following long-term
strategies can help:

# 1. Investment in Education and Skill Development
# □ Free & Quality Education: Expand access to primary, secondary, and
vocational education.
# □ Technical & Vocational Training (TVET): Equip the rural workforce
with skills in agriculture, construction, technology, and services.
# □ STEM & Digital Literacy: Encourage digital skills and coding
education to prepare youth for future job markets.
# □ Higher Education Reforms: More scholarships, affordable loans, and
state-funded universities in economically weaker states.

# Impact:
```

```
# □ Creates a skilled workforce, leading to higher wages and economic mobility.
# □ Reduces income gaps by providing equal opportunities for all.

# 2. Promotion of Entrepreneurship & MSMEs (Micro, Small & Medium Enterprises)
# □ Easy Credit & Microfinance Access: Special loans for small business owners and self-employed workers.
# □ Skill Incubation Centers: Training centers to help small businesses grow efficiently.
# □ Market Access & Digital Transformation: Connecting rural businesses to e-commerce platforms.
# □ Tax Benefits & Subsidies: Tax relief for startups in backward regions to encourage investment.

# Impact:
# □ Generates local employment, reducing migration pressure.
# □ Empowers marginalized communities through self-reliance.

# 3. Infrastructure Development in Underdeveloped Regions
# □ Connectivity: Build better roads, railways, and internet connectivity in rural areas.
# □ Smart Cities & Rural Development: Encourage smart infrastructure projects that balance urban and rural development.
# □ Industrial Hubs in Low-MPCE States: Attract businesses to invest in economically backward regions.

# Impact:
# □ Encourages investment and economic activity in lagging states.
# □ Boosts productivity and competitiveness in rural industries.

# 4. Agricultural Reforms & Rural Economic Growth
# □ Smart Farming Techniques: Promote AI, IoT, and precision farming for better yields.
# □ Farmer Producer Organizations (FPOs): Support collective farming and market linkages.
# □ Fair Pricing & Storage Facilities: Improve MSP policies and storage infrastructure.
# □ Crop Diversification: Reduce dependency on single crops, promote horticulture & organic farming.

# Impact:
# □ Increases farmer incomes, reducing rural poverty.
# □ Makes agriculture climate-resilient and profitable.

# 5. Tax Reforms & Progressive Policies
# □ Progressive Taxation: Higher taxes on ultra-rich individuals and corporations, while providing tax relief for lower-income groups.
# □ Wealth Redistribution: Strengthening social welfare schemes through fair taxation.
```

```
# □ Reducing Informal Economy: Formalizing informal jobs for social
security and fair wages.

# Impact:
# □ Narrows the wealth gap between rich and poor.
# □ Ensures funds for welfare programs without hampering growth.

# 6. Strengthening Social Security & Universal Basic Services
# □ Universal Health Coverage: Affordable healthcare reduces economic
stress on low-income groups.
# □ Affordable Housing Programs: Ensure proper housing and urban
planning.
# □ Pension & Unemployment Benefits: Financial security for senior
citizens and job seekers.

# Impact:
# □ Improves living standards and financial security.
# □ Reduces extreme poverty without discouraging productivity.

# 7. Fostering Technological & Digital Inclusion
# □ Public WiFi & Internet Access in Rural Areas
# □ Digital Banking & Financial Inclusion Programs
# □ E-Governance for Transparent Welfare Distribution

# Impact:
# □ Empowers small businesses and farmers with better access to
markets.
# □ Reduces corruption and inefficiencies in public services.

# Conclusion: Balancing Growth with Equity
# By implementing these long-term structural reforms, states can
reduce income inequality while boosting economic growth sustainably. A
combination of education, entrepreneurship, agriculture modernization,
infrastructure, fair taxation, and social security will ensure
inclusive development across all regions.

# □ Key Takeaway:
# ⚡ "Growth should not come at the cost of inequality. Equitable
policies create a sustainable economy for all."
```