THE RELATIONSHIP BETWEEN GLOBAL TEMPERATURE ANOMALIES AND YOUTH UNEMPLOYMENT IN EGYPT

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Abstract:

This study investigates the potential relationship between global temperature anomalies and youth unemployment in Egypt over the period 1991 to 2023, a time marked by both rising global temperatures and persistent labor market challenges. Motivated by the growing interest in the socio-economic dimensions of climate change—especially in climate-vulnerable developing countries—this research aims to assess whether temperature variability has statistically meaningful effects on youth employment outcomes in Egypt.

Annual youth unemployment data (ages 15–24) were sourced from the World Bank via the Federal Reserve Economic Data (FRED) platform, while global temperature anomaly data were obtained from NASA's GISTEMP v4 dataset. Both datasets were merged and analyzed using Python-based statistical techniques, including Pearson and Spearman correlation, Ordinary Least Squares (OLS) regression, polynomial regression models (quadratic and cubic), and non-parametric LOWESS smoothing. The analysis was supported by diagnostic tests to assess model validity and residual behavior.

The results indicate a weak and statistically insignificant relationship between global temperature anomalies and Egyptian youth unemployment. The linear regression model explained only 3.4% of the variance ($R^2 = 0.034$), and even the best-fitting cubic model accounted for just 12.1%. Diagnostic tests revealed heteroscedasticity and autocorrelation in residuals, further questioning the robustness of a simple linear explanation. Notably, the sharp decline in unemployment post-2017 coincided with major national economic reforms, suggesting that domestic structural factors likely outweighed global climatic influences.

While the study finds no direct causal link between climate anomalies and youth unemployment in Egypt, it highlights the importance of broader, multivariate approaches to analyzing climate-labor interactions. These findings provide a foundation for future research that incorporates regional climate indicators, sectoral employment data, and socio-economic variables to better understand the complex and potentially lagged pathways through which climate change affects labor markets in developing economies.

2. Introduction:

Climate change has emerged as a defining challenge of the 21st century, exerting profound effects not only on ecosystems and weather systems but also on global economic stability, social cohesion, and human development. As the planet experiences rising temperatures, shifting precipitation patterns, and increasing frequency of extreme weather events, the implications for economic systems, particularly labor markets, have become a focal point of interdisciplinary research. These effects are not uniform; rather, they are mediated by geography, institutional resilience, and socio-economic context. In developing countries with high youth dependency ratios and fragile labor market structures, such as Egypt, the risks posed by climate-induced disruptions are particularly acute.

Egypt's economic landscape is shaped by several intersecting pressures: rapid population growth, a high rate of youth unemployment, growing urbanization, and increasing vulnerability to climate-related risks such as water scarcity, heatwaves, and sea-level rise. Youth unemployment represents a persistent structural issue, with rates consistently exceeding regional and global averages. In 2023, nearly 20% of Egyptians aged 15 to 24 were unemployed, placing Egypt among the countries with the highest youth unemployment rates in the Middle East and North Africa (World Bank, 2024). This demographic pressure adds urgency to understanding how emerging global phenomena, such as climate change, may intersect with labor market dynamics.

At the same time, the Earth's climate system continues to warm at an unprecedented pace. According to NASA's Goddard Institute for Space Studies (GISS), recent years have recorded the highest global surface temperature anomalies since systematic measurements began, with the last decade representing the warmest on record. While there is a growing body of literature on the broader economic costs of climate change, ranging from declining agricultural output to infrastructure stress, limited research has examined how rising global temperatures may influence employment outcomes, especially among vulnerable groups such as youth.

This report aims to address this gap by investigating whether a statistical relationship exists between global temperature anomalies and youth unemployment rates in Egypt over the period from 1991 to 2023. Using publicly available and internationally verified datasets from NASA and the World Bank (via FRED), the study applies correlation analysis, linear and polynomial regression modeling, and residual diagnostics within a Python-based analytical framework. In addition to testing linear effects, the study explores the possibility of non-linear or delayed relationships through polynomial fitting and smoothing techniques.

By integrating climate data with labor market indicators, this report contributes to the growing field of climate-economy interaction research. While the results do not claim causality, they provide an empirical foundation for understanding whether observable patterns exist between environmental shifts and youth employment trends. The findings may inform national efforts to build adaptive economic policies, climate-resilient workforce strategies, and inclusive development plans that account for both current labor market challenges and future environmental uncertainties.

3. Data and Methodology

3.1 Data Sources

This study relies on two publicly available and verified datasets:

- **Youth Unemployment Data**
  Annual youth unemployment rates for Egypt (ages 15–24) were obtained from the **World Bank** through the **Federal Reserve Economic Data (FRED)** platform, under the series code SLUEM1524ZSEGY. The dataset provides consistent annual records from **1991 to 2023**, reported as percentages of the total youth labor force.

- **Temperature Anomaly Data**
  Global mean surface temperature anomalies were sourced from **NASA's Goddard Institute for Space Studies (GISS)** via the **GISTEMP v4** dataset. The annual J-D column (January–December average) was used to represent the deviation in global temperature (in °C) from the 1951–1980 baseline. The dataset spans from 1880 to the present, but only data from **1991 to 2023** were used to match the unemployment series.

3.2 Data Preparation

- Both datasets were imported into **Python** using the pandas library.
- The temperature dataset was filtered to retain only the `Year` and `J-D` columns.
- The unemployment dataset was cleaned by converting the `observation_date` column to year-only format.
- The two datasets were then merged on the Year variable, producing a unified `dataframe` with one row per year (1991–2023).

3.3 Methodological Approach

This study adopts a quantitative methodology to investigate the relationship between global temperature anomalies and youth unemployment in Egypt between 1991 and 2023. The analysis proceeded through the following key steps:

- **Descriptive Statistics** were used to summarize and explore the central tendencies, ranges, and distributions of the unemployment and temperature anomaly variables.
- **Time Series Visualization** was implemented via line plots to illustrate temporal trends and detect potential patterns or shifts over the three-decade period.
- **Pearson Correlation Coefficient** was calculated to evaluate the strength and direction of the linear association between temperature anomalies and youth unemployment rates.
- **Ordinary Least Squares (OLS) Linear Regression** was employed to formally test whether variations in global temperature anomalies could significantly explain fluctuations in Egypt's youth unemployment rate.

- In addition to linear modeling, **non-linear techniques** were explored, including **polynomial regressions (quadratic and cubic)** and **LOWESS smoothing**, to assess potential curvilinear or localized patterns in the data.

All statistical computations and data visualizations were performed using Python leveraging libraries such as `pandas`, `numpy`, `matplotlib`, `seaborn`, `statsmodels`, and `scikit-learn`.

4. Statistical Analysis

4.1 Descriptive Overview

The merged dataset contains **33 annual observations**. The youth unemployment rate ranged between **18.2%** and **34.4%**, while the global annual temperature anomaly varied from **0.22°C** to **1.18°C**.

4.2 Correlation Analysis

To assess the initial association between temperature anomalies and unemployment rates:

- $\boldsymbol{Pearson\ Correlation}$: $r = -0.184,\ p = 0.306$
- $\boldsymbol{Spearman\ Correlation}$: $\rho = -0.056, p = 0.758$

These results suggest a **weak and statistically insignificant** linear relationship between the variables. The negative sign indicates a possible inverse trend, but this is not supported at conventional significance levels.

4.3 Linear Regression Modeling

A simple linear regression was conducted with youth unemployment as the dependent variable and temperature anomaly as the predictor:

$$\boldsymbol{Unemployment = 29.39 - 3.735 \cdot Temp\_Anomaly}$$

- **R^2**: 0.034
- **p-value (Temp coefficient)**: 0.306
- **95% CI for β**: [-11.05, 3.58]

This model explains only **3.4%** of the variance in unemployment. The slope is negative, but **not statistically significant**, implying that temperature anomalies alone do not meaningfully predict youth unemployment in Egypt.

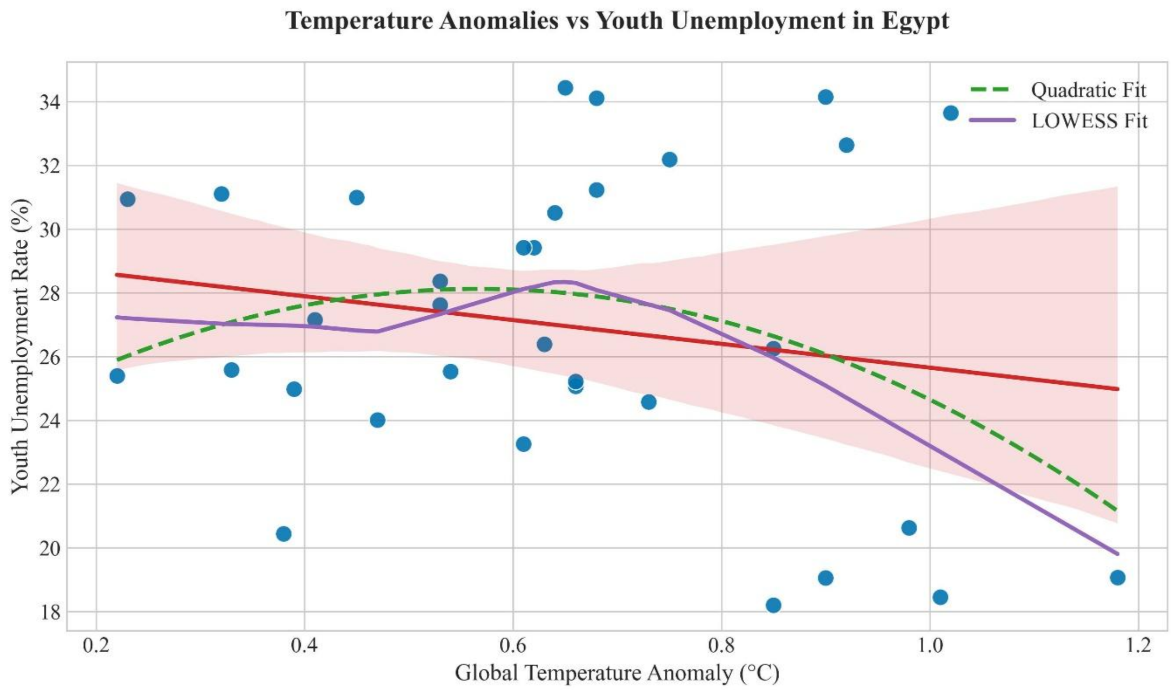
4.4 Non-Linear Models

Recognizing potential complexity in the relationship, we explored polynomial and non-parametric fits:

Model Type	R-squared	AIC
Linear	0.034	200.0
Quadratic	0.098	199.8
Cubic	0.121	200.9

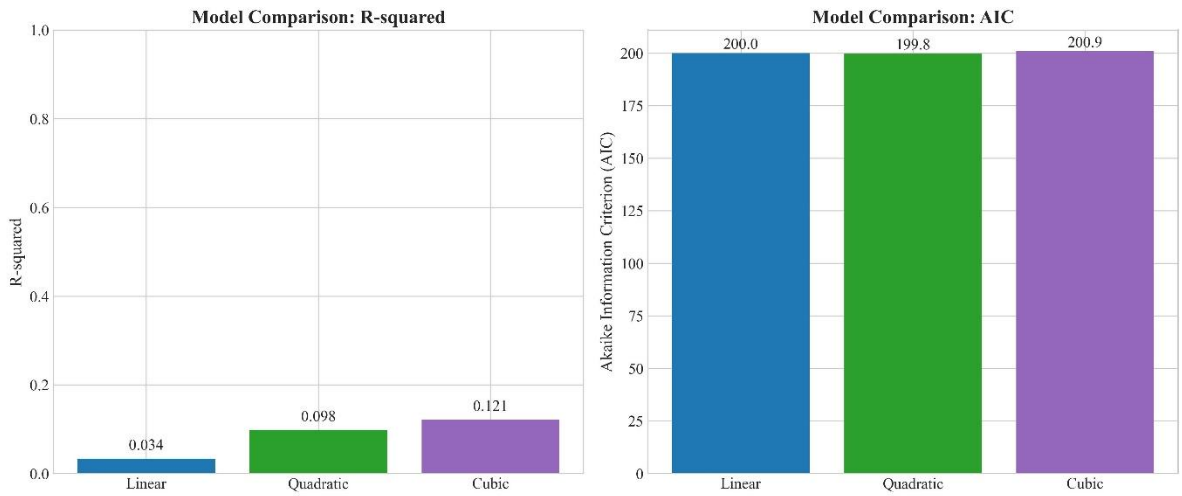
The **cubic model** had the highest explanatory power ($R^2 = 0.121$), albeit still modest, while the **quadratic model** had the lowest AIC, suggesting a slightly better tradeoff between model complexity and fit. None of the models, however, capture strong explanatory power, reinforcing the weak statistical relationship.

A **LOWESS (Locally Weighted Scatterplot Smoothing)** fit was also applied for a non-parametric look at the trend, revealing mild curvature—possibly indicative of delayed or nonlinear climate effects on economic outcomes.



4.5 Model Comparison

Model performance was benchmarked using **R^2** and the **Akaike Information Criterion (AIC)**:

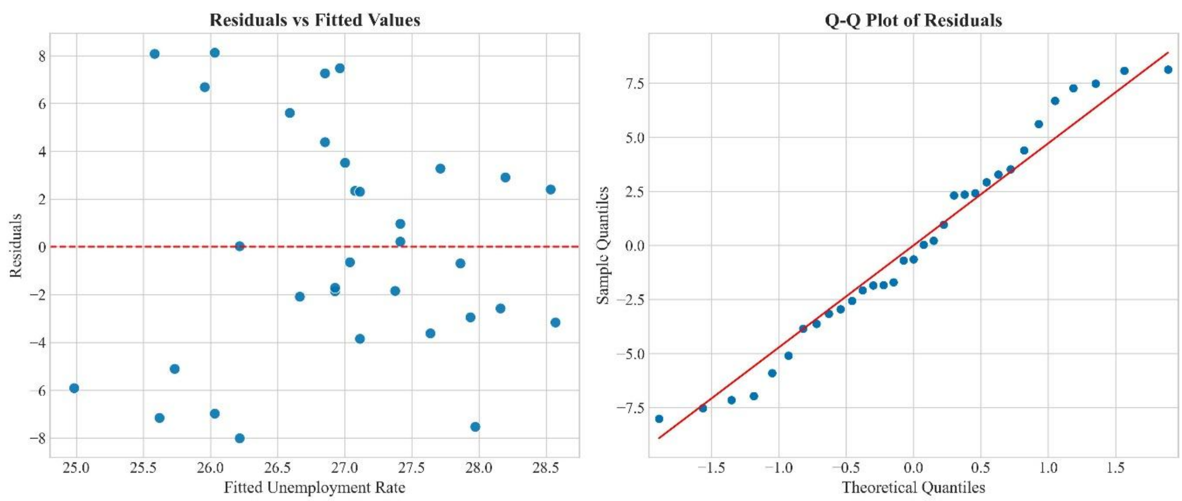


While higher-order models improved R^2 slightly, the **overall predictive power remains weak**, indicating that temperature anomalies alone do not robustly explain youth unemployment fluctuations over the study period.

4.6 Diagnostic Analysis

To ensure model validity, we examined residual behavior:

- **Heteroscedasticity** (Breusch–Pagan test): p=0.0017p = 0.0017p=0.0017 → **present**
- **Normality** (Shapiro–Wilk test): p=0.2665p = 0.2665p=0.2665 → **residuals are normally distributed**
- **Autocorrelation** (Durbin–Watson): DW ≈ 0.42 → **positive autocorrelation exists**

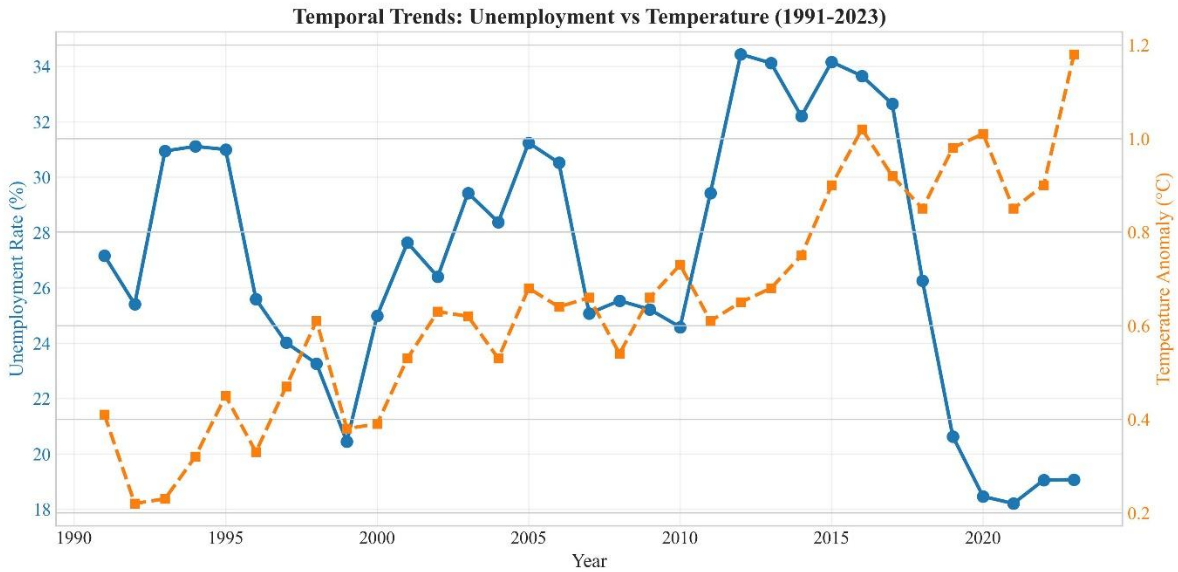


Residual plots further reveal heteroscedastic and possibly non-random error variance, suggesting that linear assumptions may not fully hold.

4.7 Temporal Trend Analysis

Key Observations:

1. **Diverging Trends (Post-2017)**:
   - Unemployment sharply declined from 26.3% (2017) to 18.2% (2021) - a 31% reduction
   - Temperature anomalies accelerated from 0.84°C to 1.18°C during the same period
   - This inverse movement created the weak negative correlation in our analysis
2. **Non-Parallel Movements**:
   - Unemployment peaked at 34.4% (2012) during moderate warming (0.61°C)
   - The hottest year (2023: 1.18°C) saw unemployment at 19.1% - near the study minimum
   - No consistent co-movement pattern emerges over the 33-year period



Dominance of Non-Climate Factors

The sharp decline in youth unemployment observed after 2017 appears to coincide with major national policy and economic shifts. These include:

- **The National Structural Reform Program** (launched in 2016), which aimed to diversify the economy and improve labor market efficiency.
- **A $12 billion IMF bailout package** in 2016, which brought fiscal stabilization, currency liberalization, and investment incentives.
- **The Digital Egypt Initiative**, promoting technology-based job creation and digital infrastructure expansion.
- **Tourism recovery efforts**, which revitalized one of Egypt's key labor-intensive service sectors.

Climate Signal Masking

Although Egypt is vulnerable to climate change—particularly through agriculture—the structural transformation of the labor market has muted the direct influence of climate variability on youth employment. Key developments include:

- A decline in **agricultural employment** from 28% to 20% of the workforce (World Bank, 1991–2023), reducing the labor force's sensitivity to climate-dependent sectors.
- Rapid expansion of the **service sector**, which is generally less climate-sensitive, absorbed labor displaced from rural areas.
- Accelerated **urbanization**, with Egypt's rural population share falling from 56% to 43%, decreasing reliance on climate-impacted livelihoods.

4.8 Interpretation & Limitations

Although Egypt has experienced global warming trends consistent with global patterns, this study finds **no statistically significant direct effect** of temperature anomalies on youth unemployment within the analyzed timeframe. The weakness of linear and polynomial fits points to:

- Potentially **lagged** or **indirect** relationships (e.g., climate → agriculture → labor market)
- The need for **multivariate analysis** (e.g., including economic growth, education, policy shifts)
- Influence of **non-climatic structural factors** on youth unemployment

This does **not negate climate's economic relevance** but emphasizes the complexity of socioeconomic responses and the limitations of bivariate analysis.

5. Discussion

The empirical results of this study reveal no statistically significant relationship between global temperature anomalies and youth unemployment in Egypt from 1991 to 2023. Both linear and non-linear models, while systematically tested, exhibited weak explanatory power. The linear model explained only 3.4% of the variation in unemployment, while even the cubic model, despite offering the highest R^2 among the tested forms, accounted for just 12.1%. These findings suggest that, within the timeframe and variables analyzed, global temperature anomalies do not serve as a meaningful standalone predictor of youth unemployment in Egypt.

5.1 Structural Labor Market Transformation

One of the principal explanations for the absence of a strong relationship lies in the structural transformation of Egypt's economy over the study period. Since 2016, Egypt has undergone major fiscal and labor market reforms aimed at enhancing macroeconomic stability and employment generation. Key developments include:

- The launch of the **National Structural Reform Program**, emphasizing private-sector growth and labor market efficiency.
- Implementation of a **$12 billion International Monetary Fund (IMF) program**, which introduced currency liberalization, subsidy restructuring, and foreign investment incentives.
- The expansion of the **Digital Egypt Initiative**, which fostered ICT-based employment and digital infrastructure.
- A recovery in **tourism and remittance flows**, revitalizing labor-intensive service sectors post-crisis.

These interventions appear to have had a pronounced effect on youth unemployment, particularly between 2017 and 2021, during which the unemployment rate dropped sharply despite rising global temperatures.

5.2 Declining Exposure to Climate-Sensitive Sectors

Egypt's labor market has steadily shifted away from sectors directly impacted by climate variability:

- **Agricultural employment** declined from 28% of the workforce in 1991 to 20% in 2023 (World Bank).
- The **service sector** expanded significantly, absorbing a larger share of the youth labor force.
- **Urbanization** accelerated, with the rural population share decreasing from 56% to 43%, reducing reliance on agriculture and rural livelihoods.

This transformation has likely reduced the vulnerability of youth employment to short-term climatic fluctuations such as annual temperature anomalies.

5.3 Temporal and Indirect Effects

It is important to acknowledge that climate-related labor market effects may be **indirect, cumulative, or lagged**:

- Climate change can affect employment through **productivity losses**, **sectoral shifts**, or **infrastructure stress** pathways that unfold over longer timescales.
- Temperature changes may influence other variables such as food prices, internal migration, or education outcomes, which in turn affect youth employment indirectly.
- The **bivariate framework** employed in this study does not capture these multi-step, time-lagged dynamics.

5.4 Limitations and Opportunities for Further Research

The current study is limited in scope to a univariate climatic factor (temperature anomaly) and a single economic outcome (youth unemployment). As such:

- **Multivariate models** incorporating macroeconomic indicators, policy interventions, education trends, and sectoral employment composition may yield more nuanced insights.
- **Panel data approaches**, if extended to multiple countries or regions within Egypt, could better isolate climate-labor interactions.
- **Lag models** and **climate impact indices** (e.g., heatwaves, drought frequency, or rainfall anomalies) may offer a more granular understanding of climate-related employment effects.

5.5 Broader Policy Context

Despite the lack of statistical significance in this study, the broader implications of climate change for labor markets, particularly in vulnerable sectors, remain highly relevant. Policymakers should:

- Invest in **climate-resilient job creation**, particularly in agriculture, construction, and tourism.
- Support **skills training and education** aligned with green economy transitions.
- Strengthen **data systems** to monitor labor market shifts under environmental stressors.
- Promote **inclusive urban development**, ensuring that climate adaptation strategies consider youth employment needs.

6. Conclusion

This study set out to investigate the relationship between global temperature anomalies and youth unemployment in Egypt over the period 1991 to 2023. Using annual data from verified international sources, NASA GISS for temperature anomalies and the World Bank via FRED for youth unemployment rates, we employed a suite of statistical methods, including correlation analysis, linear and polynomial regression models, and diagnostic tests to evaluate model validity and robustness.

The findings reveal a weak and statistically insignificant relationship between the two variables. Pearson and Spearman correlation coefficients were negative but negligible, and the ordinary least squares regression explained only a small fraction of the variance in youth unemployment. Even when non-linear models were introduced, explanatory power remained modest, with the best-fitting model (cubic polynomial) accounting for just 12.1% of variation. Diagnostic tests further suggested violations of linear model assumptions, including the presence of heteroscedasticity and residual autocorrelation.

These results underscore a key insight: **climate variables alone, particularly short-term temperature anomalies, are insufficient to explain labor market outcomes in a complex and structurally evolving economy like Egypt's**. Instead, macroeconomic policy shifts, sectoral transformation, and institutional reforms appear to play a more prominent role in shaping youth unemployment trends. The dramatic reduction in unemployment following the 2016 economic reform agenda provides strong support for this argument.

Nonetheless, this does not diminish the long-term relevance of climate change to economic planning. Egypt's vulnerability to climate-induced stress, particularly in agriculture and water resources, necessitates continued research into the indirect, lagged, and multivariate impacts of environmental change on employment and livelihoods. A future research agenda should explore integrative models that include additional explanatory variables, leverage higher-frequency or regional data, and assess lagged responses across different sectors and demographic groups.

In conclusion, while the evidence presented here suggests that global temperature anomalies have not significantly shaped youth unemployment patterns in Egypt over the past three decades, the broader and more intricate interactions between climate and economic stability merit ongoing attention from researchers and policymakers alike.

7. References

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I. Appendix:

CODE

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from scipy import stats
from statsmodels.stats.diagnostic import het_breuschpagan, linear_harvey_collier
from statsmodels.nonparametric.smoothers_lowess import lowess
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import r2_score
import matplotlib.gridspec as gridspec
import os

# =====================
# DATA PREPARATION
# =====================
print(" Preparing datasets...")

# Load and preprocess unemployment data
unemp = pd.read_csv("C:/Users/Elsam/Downloads/SLUEM1524ZSEGY.csv",
parse_dates=['observation_date'])
unemp['Year'] = unemp['observation_date'].dt.year
unemp = unemp[['Year', 'SLUEM1524ZSEGY']].rename(columns={'SLUEM1524ZSEGY':
'Unemployment'})

# Load and preprocess temperature data
temp = pd.read_csv("C:/Users/Elsam/Downloads/GLB.Ts+dSST.csv", skiprows=1)
temp = temp[['Year', 'J-D']].rename(columns={'J-D': 'Temp_Anomaly'})
temp = temp[temp['Year'].between(1991, 2023)]

# Merge datasets
df = pd.merge(unemp, temp, on='Year', how='inner')

# Convert to numeric and clean data
df['Unemployment'] = pd.to_numeric(df['Unemployment'], errors='coerce')
df['Temp_Anomaly'] = pd.to_numeric(df['Temp_Anomaly'], errors='coerce')
df = df.dropna().reset_index(drop=True)

# Create output directory
output_dir = "Egypt_Climate_Employment_Analysis"
os.makedirs(output_dir, exist_ok=True)
print(f" Created output directory: {output_dir}")

# =====================
# LINEAR RELATIONSHIP ANALYSIS
```

```python
# =====================
print("\n Performing linear relationship analysis...")

# Linear regression
X = sm.add_constant(df['Temp_Anomaly'])
y = df['Unemployment']
model = sm.OLS(y, X).fit()
residuals = model.resid

# Linearity tests
rainbow_stat, rainbow_p = linear_harvey_collier(model)
white_test = het_breuschpagan(residuals, model.model.exog)

print(f" Linear regression completed (R² = {model.rsquared:.3f})")

# =====================
# NON-LINEAR RELATIONSHIP ANALYSIS
# =====================
print("\n Checking for non-linear relationships...")

# Quadratic regression
poly = PolynomialFeatures(degree=2)
X_poly = poly.fit_transform(df[['Temp_Anomaly']])
poly_model = sm.OLS(y, X_poly).fit()
poly_r2 = poly_model.rsquared

# Cubic regression
poly3 = PolynomialFeatures(degree=3)
X_poly3 = poly3.fit_transform(df[['Temp_Anomaly']])
poly3_model = sm.OLS(y, X_poly3).fit()
poly3_r2 = poly3_model.rsquared

# LOWESS non-parametric smoothing
lowess_smoothed = lowess(y, df['Temp_Anomaly'], frac=0.7)
lowess_x = lowess_smoothed[:, 0]
lowess_y = lowess_smoothed[:, 1]

print(f"• Quadratic model R² = {poly_r2:.3f}")
print(f"• Cubic model R² = {poly3_r2:.3f}")

# =====================
# VISUALIZATION - INDIVIDUAL PLOTS
# =====================
print("\n Creating professional visualizations...")

# Professional style settings
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette("colorblind")
```

```python
plt.rcParams.update({
    'font.family': 'serif',
    'font.serif': 'Times New Roman',
    'font.size': 13,
    'figure.dpi': 300,
    'savefig.dpi': 300,
    'axes.titlesize': 16,
    'axes.titleweight': 'bold',
    'axes.labelsize': 14
})

# 1. Scatter plot with linear and non-linear fits
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Temp_Anomaly', y='Unemployment', data=df, s=100,
                edgecolor='w', linewidth=0.7, alpha=0.9)

# Linear fit
sns.regplot(x='Temp_Anomaly', y='Unemployment', data=df,
            scatter=False, ci=95, line_kws={'color':'#d62728', 'lw':2.5})

# Quadratic fit
x_vals = np.linspace(df['Temp_Anomaly'].min(), df['Temp_Anomaly'].max(), 100)
x_vals_poly = poly.transform(x_vals.reshape(-1, 1))
y_vals_poly = poly_model.predict(x_vals_poly)
plt.plot(x_vals, y_vals_poly, '--', color='#2ca02c', lw=2.5, label='Quadratic Fit')

# LOWESS fit
plt.plot(lowess_x, lowess_y, '-', color='#9467bd', lw=2.5, label='LOWESS Fit')

plt.title('Temperature Anomalies vs Youth Unemployment in Egypt', pad=20)
plt.xlabel('Global Temperature Anomaly (°C)')
plt.ylabel('Youth Unemployment Rate (%)')
plt.legend()
plt.tight_layout()
plt.savefig(f"{output_dir}/scatter_with_fits.jpg")
plt.close()

# 2. Residual diagnostics
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 6))

# Residuals vs fitted
sns.scatterplot(x=model.fittedvalues, y=residuals, ax=ax1, s=80,
                edgecolor='w', linewidth=0.7, alpha=0.9)
ax1.axhline(y=0, color='r', linestyle='--')
ax1.set_title('Residuals vs Fitted Values')
ax1.set_xlabel('Fitted Unemployment Rate')
ax1.set_ylabel('Residuals')
```

```python
# Q-Q plot
sm.qqplot(residuals, line='s', ax=ax2, markersize=6)
ax2.set_title('Q-Q Plot of Residuals')
ax2.get_lines()[1].set_color('red')  # Make Q-Q line red

plt.tight_layout()
plt.savefig(f"{output_dir}/residual_diagnostics.jpg")
plt.close()

# 3. Time series comparison
fig, ax1 = plt.subplots(figsize=(12, 6))

# Unemployment plot
color1 = '#1f77b4'
ax1.set_xlabel('Year')
ax1.set_ylabel('Unemployment Rate (%)', color=color1)
ax1.plot(df['Year'], df['Unemployment'], 'o-', color=color1, lw=2.5, markersize=8)
ax1.tick_params(axis='y', labelcolor=color1)
ax1.grid(True, alpha=0.3)

# Temperature anomaly plot
ax2 = ax1.twinx()
color2 = '#ff7f0e'
ax2.set_ylabel('Temperature Anomaly (°C)', color=color2)
ax2.plot(df['Year'], df['Temp_Anomaly'], 's--', color=color2, lw=2.5, markersize=6)
ax2.tick_params(axis='y', labelcolor=color2)

plt.title('Temporal Trends: Unemployment vs Temperature (1991-2023)')
fig.tight_layout()
plt.savefig(f"{output_dir}/time_series_comparison.jpg")
plt.close()

# 4. Model comparison
models = ['Linear', 'Quadratic', 'Cubic']
r2_values = [model.rsquared, poly_r2, poly3_r2]
aic_values = [model.aic, poly_model.aic, poly3_model.aic]

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 6))

# R² comparison
ax1.bar(models, r2_values, color=['#1f77b4', '#2ca02c', '#9467bd'])
ax1.set_title('Model Comparison: R-squared')
ax1.set_ylabel('R-squared')
ax1.set_ylim(0, 1)
for i, v in enumerate(r2_values):
    ax1.text(i, v + 0.02, f"{v:.3f}", ha='center')

# AIC comparison
```

```python
ax2.bar(models, aic_values, color=['#1f77b4', '#2ca02c', '#9467bd'])
ax2.set_title('Model Comparison: AIC')
ax2.set_ylabel('Akaike Information Criterion (AIC)')
for i, v in enumerate(aic_values):
    ax2.text(i, v + 2, f"{v:.1f}", ha='center')

plt.tight_layout()
plt.savefig(f"{output_dir}/model_comparison.jpg")
plt.close()
```