Suicide and Unemployment in Socioeconomic Spatial Patterns

Abstract

According to the World Health Organisation, one in every 100 deaths in 2019 were due to death by suicide. There are many causes that explain the suicide rates across the world. Socioeconomic situations such as unemployment, is one cause that is climbing up to the top reasons for committing suicide since the Great Recession. Using Linear Regression analysis, the relationship between the suicide mortality rate and unemployment for different regions can be found so as to determine the effect of geographically centered socioeconomic events on suicides. From the study, regions with high suicide mortality rates is a result of high unemployment levels found in the region.

1 INTRODUCTION

Suicidal behaviour has seen a rampant growth over the last decade or two. While the prevention of suicide is a tireless effort, the causes for the same vary greatly across all issues. Bipolar disorder is the most common cause for suicides. Apart from mental health disorders, socioeconomic events also seem to have an effect on the suicide mortality rate. Since the Great Recession in 2007-09, casual relationships between unemployment and suicide have started to form. (Nordt, Warnke, Seifritz, & Kawohl, 2015) states that unemployment has a direct effect on the physical health of an individual. The paper explores the relationship between the suicide rates and unemployment by analysing global public data across world regions. Their model predicted a higher suicide rate following a fall in the employment levels across 63 countries. There have been certified studies that talk about the inverse relationship between suicide and socioeconomic standing.

(Rehkopf & Buka, 2006) explored the socioeconomic characteristics affecting area suicide rates. Their results concluded lower suicide rates in areas with higher socioeconomic status. (Vijayakumar, Nagaraj, Pirkis, & Whiteford, 2005) explores the association of suicide with socioeconomic indicators in developing countries. Suicide is a vital problem in the developing countries. The political and economic situations plays an important role in the suicide rates. (Cantor & Slater, 1997) studied the effect of economic disadvantage and suicide rate in Queensland. The results showed a positive correlation between the two.

Unemployment creates social fragmentation that increases the risk of suicide. Different regions of the world have different measures of success and different levels of socioeconomic status. Suicide is prevalent in all regions of the world. However, unemployment may not be one of the important reasons for it in every region and in some regions, there might not be any causation between the two. The political and economical diversity between the countries can account for the presence of unemployment in various regions. Does unemployment affect suicide rates in all regions of the world to the same effect?

2 DATA AND METHODOLOGY

The data used for this study was collected from World Bank. (*Health Nutrition and population statistics*, n.d.) The indicators in the data belong to Health, Nutrition and Population statistics. For the years 2002 to 2019, the data consists of the total unemployment as a percentage of the total labour force and the mortality rate due to suicide per 100,000 population for the various regions of the world split into 13 wide areas namely, Africa Eastern and Southern, Africa Western and Central, Arab World, Caribbean small states, Central Europe and the Baltics, East Asia & Pacific, Euro area, Europe & Central Asia, European Union, Latin America & Caribbean, Middle East & North Africa, Pacific island small states, and Sub-Saharan Africa.

We can find the various linear relationships in all these regions for unemployment and suicide. These relationships can then be compared against each other to find the regions where unemployment was one of the major reasons for suicide. In simple linear regression, the relationship between the predictor and the response is described. The general model for linear regression is

$$y = mx + c$$

where y is the dependent variable i.e. predictor (in this case, the suicide mortality rate)
x is the independent variable i.e. response (in this case, the unemployment)
m is the slope and c is the intercept

Using Python, data for these different regions were filtered into different data frames using the pandas package. Using the sklearn package, the linear regression analysis was used to find the relationship between the unemployment and suicide rates in the different regions. Using the seaborn package, the various points for suicide and unemployment can be plotted, along with the linear relationship between the two. (See A)

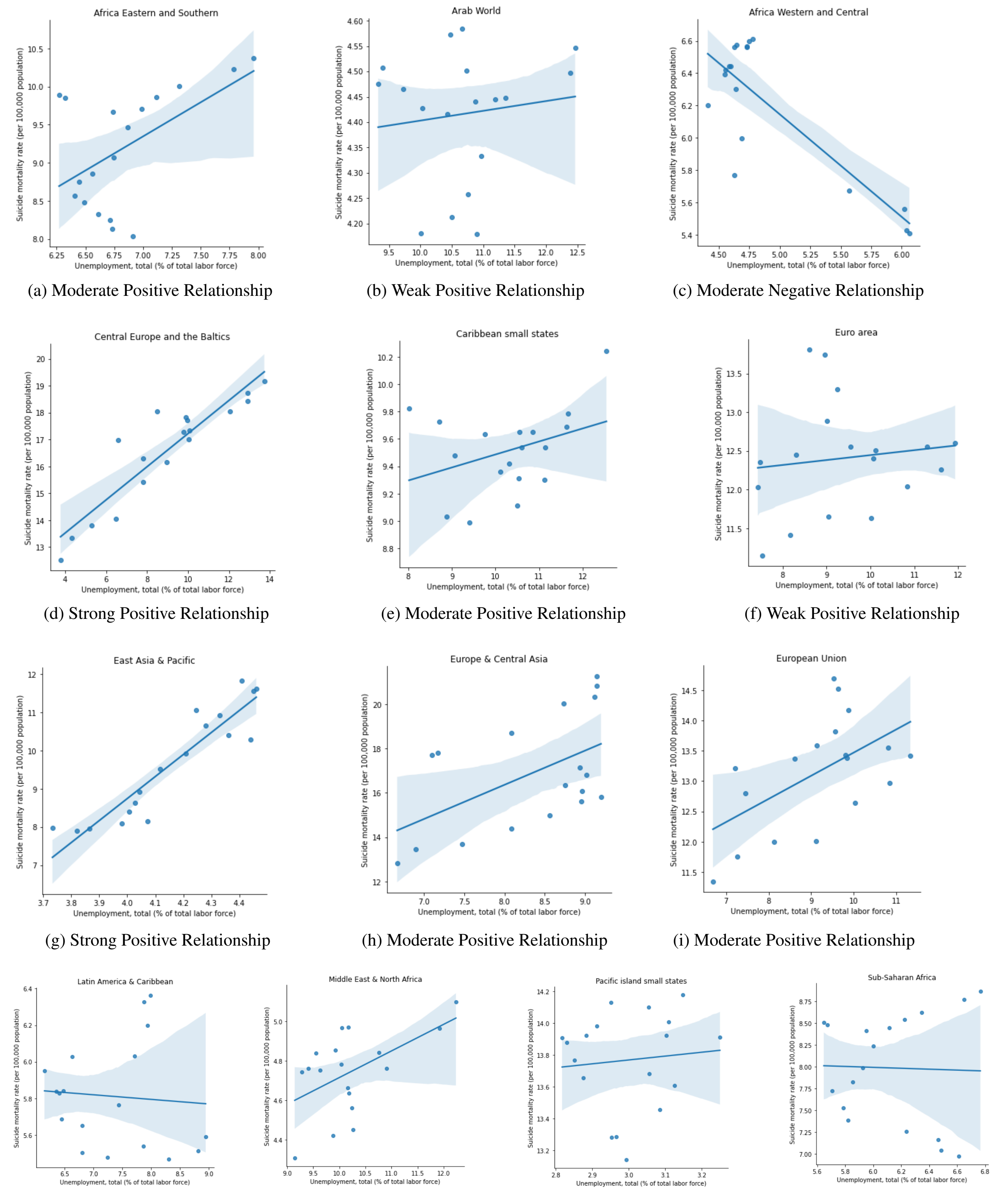
3 RESULTS AND ANALYSIS

The 13 regions cover all the areas of the world. Through linear regression analysis, the various relationships between suicide mortality rate and unemployment can be found as seen in Table 1. A positive relationship indicates that as there is a direct relationship between the two i.e. as unemployment increases, there is a rise in the suicide mortality rate. A negative relationship indicates an indirect relationship i.e. as unemployment increases, there is a fall in the suicide mortality rate. Using Python's sklearn package, we can find the linear model between the two for all 13 regions. The regression model for the various regions are

1. Africa Eastern and Southern Region: $y = 0.89 * x + 3.07$
2. Arab World: $y = 0.01 * x + 4.21$
3. Africa Western and Central: $y = -0.63 * x + 9.31$
4. Central Europe and the Baltics: $y = 0.61 * x + 11.05$
5. Caribbean Small States: $y = 0.09 * x + 8.53$
6. Euro Area: $y = 0.06 * x + 11.81$
7. East Asia & Pacific: $y = 5.76 * x - 14.33$
8. Europe & Central Asia: $y = 1.54 * x + 3.98$
9. European Union: $y = 0.38 * x + 9.64$
10. Latin America & Caribbean: $y = -0.02 * x + 5.99$
11. Middle East & North Africa: $y = 0.13 * x + 3.36$
12. Pacific Island Small States: $y = 0.24 * x + 13.03$
13. Sub-Saharan Africa: $y = -0.05 * x + 8.30$

Regions	Relationship	Strength
Africa Eastern and Southern Region	Positive	Moderate
Arab World	Positive	Weak
Africa Western and Central	Negative	Moderate
Central Europe and the Baltics	Positive	Strong
Caribbean Small States	Positive	Moderate
Euro Area	Positive	Weak
East Asia & Pacific	Positive	Strong
Europe & Central Asia	Positive	Moderate
European Union	Positive	Moderate
Latin America & Caribbean	Negative	Weak
Middle East & North Africa	Positive	Moderate
Pacific Island Small States	Positive	Weak
Sub-Saharan Africa	Negative	Weak

Table 1: Linear Relationships between Suicide rates and Unemployment for 13 different regions



(a) Moderate Positive Relationship (b) Weak Positive Relationship (c) Moderate Negative Relationship

(d) Strong Positive Relationship (e) Moderate Positive Relationship (f) Weak Positive Relationship

(g) Strong Positive Relationship (h) Moderate Positive Relationship (i) Moderate Positive Relationship

(j) Weak Negative Relationship (k) Moderate Positive Relationship (l) Weak Positive Relationship (m) Weak Negative Relationship

Figure 1: Simple Linear Regression Lines for Different Regions

From the models, we can find the direction of the relationship i.e. positive or negative. The regions of Africa Western and Central, Latin America & Caribbean, and Sub-Saharan Africa show a negative relationship. The strength of this relationship is either moderate or weak as seen in Figure 1. From the data, it is seen that the unemployment rate in the Africa Western and Central region was lesser than 5% for the major part of the decade. In the Latin American region and the Sub-Saharan African region has an unemployment level above 5%. Compared to the rest of the regions, these three have a relatively low suicide mortality rate (4 to 7) per 100,000 population.

The regions with strong positive relationship (i.e. Central Europe and the Baltics & East Asia and Pacific) have higher unemployment levels and high suicide mortality rates among the rest. By calculating the coefficient of determination, we can see that in both these regions, over 80% of suicides can be explained as a cause of unemployment in the region.

The unemployment levels for the moderately positive regions are between 2 to 12% of the total labour force and the suicide rates are between 4 and 20 per 100,000 population. These do not vary greatly over the span of the decade. These regions consists of a mix of developed, developing and underdeveloped countries. The relationship might be affected by various other factors including the spatial patterns of socioeconomic situations.

4 CONCLUSIONS

(Blakely, Collings, & Atkinson, 2003) states, "Being unemployed was associated with a twofold to threefold increased relative risk of death by suicide, compared with being employed." The resulting observations from the analysis indicates that regions with high unemployment rates results in a high suicide mortality rate. A few regions with low unemployment levels and low suicide rates had a negative relationship indicating the presence of other factors that possibly affect the suicide mortality rate besides unemployment. Unemployment may not play a major role in the suicide rates of these regions.

One substantial question that is essential to ask is if the effect of unemployment on suicide rates is affected by any past experiences or incidences of mental health. (Milner, Page, & LaMontagne, 2014) argued that before controlling for prior mental health cases, unemployment had a significant higher risk on suicide. However, after controlling for mental health, the relative risk reduced by 37%. The results in this study has not been controlled for mental health issues. Hence, the results may not be entirely accurate.

One of the issues arising from the quality of the data is the inability to compare them with other countries. There are other factors apart from regions that are essential for complete analysis that has been overlooked due to lack of data. For over 50% of the world's countries and a third of its population, there is a lack of data relating to suicide (Vijayakumar et al., 2005). Countries with highest population had enough data to compensate for unavailable data in low HDI countries. (Kuroki, 2010) confirms that unemployment confirms the increase of male suicide rates. However, the results for female suicide rates are inconclusive. (Cantor & Slater, 1997) found different relationships between economic advantages and suicide in different regions in Queensland. However, while considering the overall relationship between the two in all of Queensland, the results weren't promising. The results in this paper might not be completely accurate considering the wider area of the regions. There may be variability of the relationship within countries and places in the area groupings considered.

References

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Appendix A CODE

```
#Importing packages
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#Reading in the csv file
df = pd.read_csv('SuicideAndUnemployment.csv', encoding='UTF-8')

#Deleting unnessecary columns
del df["Series Code"]
del df["Country Code"]

#Filtering data frames by different regions
df_1 = df[df["Country Name"] == "Africa Eastern and Southern"]
df_2 = df[df["Country Name"] == "Africa Western and Central"]
df_3 = df[df["Country Name"] == "Arab World"]
df_4 = df[df["Country Name"] == "Caribbean small states"]
df_5 = df[df["Country Name"] == "Central Europe and the Baltics"]
df_6 = df[df["Country Name"] == "East Asia & Pacific"]
df_7 = df[df["Country Name"] == "Euro area"]
df_8 = df[df["Country Name"] == "Europe & Central Asia"]
df_9 = df[df["Country Name"] == "European Union"]
df_10 = df[df["Country Name"] == "Latin America & Caribbean"]
df_11 = df[df["Country Name"] == "Middle East & North Africa"]
df_12 = df[df["Country Name"] == "Pacific island small states"]
df_13 = df[df["Country Name"] == "Sub-Saharan Africa"]

#Deleting Regions of the world
del df_1["Country Name"]
del df_2["Country Name"]
del df_3["Country Name"]
del df_4["Country Name"]
del df_5["Country Name"]
del df_6["Country Name"]
del df_7["Country Name"]
del df_8["Country Name"]
del df_9["Country Name"]
del df_10["Country Name"]
del df_11["Country Name"]
del df_12["Country Name"]
del df_13["Country Name"]

#Wider to Longer
df_1t = pd.melt(df_1, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
df_2t = pd.melt(df_2, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
df_3t = pd.melt(df_3, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
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    df_4t = pd.melt(df_4, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_5t = pd.melt(df_5, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_6t = pd.melt(df_6, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_7t = pd.melt(df_7, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_8t = pd.melt(df_8, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_9t = pd.melt(df_9, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_10t = pd.melt(df_10, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_11t = pd.melt(df_11, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_12t = pd.melt(df_12, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])
    df_13t = pd.melt(df_13, id_vars=['Series Name'], value_vars=['2002 [YR2002]', '2003 [YR2003]', '2004 [YR2004]', '2005 [YR2005]', '2006 [YR2006]', '2007 [YR2007]', '2008 [YR2008]', '2009 [YR2009]', '2010 [YR2010]', '2011 [YR2011]', '2012 [YR2012]', '2013 [YR2013]', '2014 [YR2014]', '2015 [YR2015]', '2016 [YR2016]', '2017 [YR2017]', '2018 [YR2018]', '2019 [YR2019]'])

    #Longer to Wider
    df_aes = pd.pivot(df_1t, index='variable', columns='Series Name', values='value')
    df_aws = pd.pivot(df_2t, index='variable', columns='Series Name', values='value')
    df_aw = pd.pivot(df_3t, index='variable', columns='Series Name', values='value')
    df_css = pd.pivot(df_4t, index='variable', columns='Series Name', values='value')
    df_ceb = pd.pivot(df_5t, index='variable', columns='Series Name', values='value')
    df_eap = pd.pivot(df_6t, index='variable', columns='Series Name', values='value')
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    df_ea = pd.pivot(df_7t, index='variable', columns='Series Name', values='value')
    df_eca = pd.pivot(df_8t, index='variable', columns='Series Name', values='value')
    df_eu = pd.pivot(df_9t, index='variable', columns='Series Name', values='value')
    df_lac = pd.pivot(df_10t, index='variable', columns='Series Name', values='value')
    df_mena = pd.pivot(df_11t, index='variable', columns='Series Name', values='value')
    df_pss = pd.pivot(df_12t, index='variable', columns='Series Name', values='value')
    df_ssa = pd.pivot(df_13t, index='variable', columns='Series Name', values='value')

    #Plotting Regression Lines
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_aes).set(title='Africa Eastern and Southern')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_aws).set(title='Africa Western and Central')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_aw).set(title='Arab World')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_css).set(title='Caribbean small states')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_ceb).set(title='Central Europe and the Baltics')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_eap).set(title='East Asia & Pacific')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_ea).set(title='Euro area')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_eca).set(title='Europe & Central Asia')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_eu).set(title='European Union')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_lac).set(title='Latin America & Caribbean')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_mena).set(title='Middle East & North Africa')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_pss).set(title='Pacific island small states')
    sns.lmplot("Unemployment, total (% of total labor force)", "Suicide mortality rate (per 100,000 population)", df_ssa).set(title='Sub-Saharan Africa')

    #Africa Eastern and Southern Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_aes[['Unemployment, total (% of total labor force)']]
    y = df_aes[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Africa Eastern and Southern R Square
    from sklearn import metrics

    x = df_aes[['Unemployment, total (% of total labor force)']]
    y = df_aes[['Suicide mortality rate (per 100,000 population)']]
```

```
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Africa Western and Central Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_aws[['Unemployment, total (% of total labor force)']]
    y = df_aws[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Africa Western and Central R Square
    from sklearn import metrics

    x = df_aws[['Unemployment, total (% of total labor force)']]
    y = df_aws[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Arab World Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_aw[['Unemployment, total (% of total labor force)']]
    y = df_aw[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Arab World R square
    from sklearn import metrics

    x = df_aw[['Unemployment, total (% of total labor force)']]
    y = df_aw[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Caribbean small states Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_css[['Unemployment, total (% of total labor force)']]
    y = df_css[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Caribbean small states R Square
```

```
    from sklearn import metrics

    x = df_css[['Unemployment, total (% of total labor force)']]
    y = df_css[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Central Europe and the Baltics Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_ceb[['Unemployment, total (% of total labor force)']]
    y = df_ceb[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Central Europe and the Baltics R Square
    from sklearn import metrics

    x = df_ceb[['Unemployment, total (% of total labor force)']]
    y = df_ceb[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #East Asia & Pacific Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_eap[['Unemployment, total (% of total labor force)']]
    y = df_eap[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #East Asia & Pacific R Square
    from sklearn import metrics

    x = df_eap[['Unemployment, total (% of total labor force)']]
    y = df_eap[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Euro area Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_ea[['Unemployment, total (% of total labor force)']]
    y = df_ea[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

```

```
    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Euro area R Square
    from sklearn import metrics

    x = df_ea[['Unemployment, total (% of total labor force)']]
    y = df_ea[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Europe & Central Asia Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_eca[['Unemployment, total (% of total labor force)']]
    y = df_eca[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Europe & Central Asia R Square
    from sklearn import metrics

    x = df_eca[['Unemployment, total (% of total labor force)']]
    y = df_eca[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #European Union Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_eu[['Unemployment, total (% of total labor force)']]
    y = df_eu[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #European Union R Square
    from sklearn import metrics

    x = df_eu[['Unemployment, total (% of total labor force)']]
    y = df_eu[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Latin America & Caribbean Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_lac[['Unemployment, total (% of total labor force)']]
```

```
    y = df_lac[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Latin America & Caribbean R Square
    from sklearn import metrics

    x = df_lac[['Unemployment, total (% of total labor force)']]
    y = df_lac[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Middle East & North Africa Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_mena[['Unemployment, total (% of total labor force)']]
    y = df_mena[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Middle East & North Africa R Square
    from sklearn import metrics

    x = df_mena[['Unemployment, total (% of total labor force)']]
    y = df_mena[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Pacific island small states Regression
    from sklearn.linear_model import LinearRegression

    est = LinearRegression(fit_intercept = True)

    x = df_pss[['Unemployment, total (% of total labor force)']]
    y = df_pss[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Pacific island small states R Square
    from sklearn import metrics

    x = df_pss[['Unemployment, total (% of total labor force)']]
    y = df_pss[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))

    #Sub-Saharan Africa Regression
    from sklearn.linear_model import LinearRegression
```

```
    est = LinearRegression(fit_intercept = True)

    x = df_ssa[['Unemployment, total (% of total labor force)']]
    y = df_ssa[['Suicide mortality rate (per 100,000 population)']]

    est.fit(x, y)

    print("Coefficients:", est.coef_)
    print ("Intercept:", est.intercept_)

    #Sub-Saharan Africa R Square
    from sklearn import metrics

    x = df_ssa[['Unemployment, total (% of total labor force)']]
    y = df_ssa[['Suicide mortality rate (per 100,000 population)']]
    model = LinearRegression()
    model.fit(x, y)
    y_hat = model.predict(x)
    print ("R^2:", metrics.r2_score(y_hat, y))
```