Modeling Mental Health Illness

Overview

The goal of this project is to model depression rates in the U.S. This is useful not only for government agencies, but also to better understand what else is correlated with depression. Having a better forecast for depression will allow the government to allocate additional funds to fight the mental health crises. The final project is useful to any mental health organization or government agency that can advocate or provide support for those with depression.

Business Understanding

Depression rates in the U.S. have grown significantly in the past two years during Covid. This has a tremendous impact on not only those who experience this disease, it affects those around them, and the Economy as a whole. According to a 2018 study by [PharmaEconomics (https://link.springer.com/article/10.1007/s40273-021-01019-4)](https://link.springer.com/article/10.1007/s40273-021-01019-4), depression cost the U.S. economy $326 billion in 2018. This number is rising, not only because of rising rates but because those with the disease are not willing or in many cases unable to receive proper care.

By modeling Depression Rates more accurately, the CDC will be able to more confidently secure increased funding to help improve the lives of those with this disease and therefore ease the economic and psychological burden of U.S. citizens.

In [1]:

```python
import pandas as pd
import numpy as np
pd.set_option('display.max_rows', 10)
from datetime import datetime as dt

import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error

import seaborn as sns
from statsmodels.tsa.stattools import adfuller
from sklearn.model_selection import TimeSeriesSplit
plt.style.use('ggplot')

#statsmodels
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import acf, pacf, adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
import itertools
```

In [2]:
```
#Load Data
mental_disorder_df = pd.read_csv('data/prevalence-by-mental-and-substanc
```

In [3]:
```
#View Data
mental_disorder_df
```

Out[3]:

	Entity	Code	Year	Prevalence - Schizophrenia - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Bipolar disorder - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Eating disorders - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Anxiety disorders - Sex: Both - Age: Age-standardized (Percent)	Preva D dis Sex Ag stand (P
0	Afghanistan	AFG	1990	0.228979	0.721207	0.131001	4.835127	0
1	Afghanistan	AFG	1991	0.228120	0.719952	0.126395	4.821765	0
2	Afghanistan	AFG	1992	0.227328	0.718418	0.121832	4.801434	0
3	Afghanistan	AFG	1993	0.226468	0.717452	0.117942	4.789363	0
4	Afghanistan	AFG	1994	0.225567	0.717012	0.114547	4.784923	0
...	...	...	...	...	...	...	...	
6835	Zimbabwe	ZWE	2015	0.209359	0.560882	0.099610	3.315701	0
6836	Zimbabwe	ZWE	2016	0.209979	0.561768	0.100821	3.324230	0
6837	Zimbabwe	ZWE	2017	0.210631	0.562612	0.101671	3.330569	0
6838	Zimbabwe	ZWE	2018	0.211237	0.563283	0.102398	3.317500	0
6839	Zimbabwe	ZWE	2019	0.211969	0.563820	0.102902	3.283934	0

6840 rows × 10 columns

In [4]:

```python
#Isolate only the U.S. Data
us_df = mental_disorder_df.loc[mental_disorder_df['Entity'] == 'United St
us_df
```

Out[4]:

	Entity	Code	Year	Prevalence - Schizophrenia - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Bipolar disorder - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Eating disorders - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Anxiety disorders - Sex: Both - Age: Age-standardized (Percent)	Preva Dr diso Sex: Ag standa (P
6330	United States	USA	1990	0.467115	0.649644	0.433047	5.617003	2.:
6331	United States	USA	1991	0.472488	0.651606	0.450069	5.636548	2.:
6332	United States	USA	1992	0.477502	0.653518	0.465582	5.661951	2.:
6333	United States	USA	1993	0.481847	0.655238	0.478267	5.691142	2.:
6334	United States	USA	1994	0.485216	0.656640	0.487285	5.722273	2..

In [5]:

```python
#Set Index to the year
us_df = us_df.set_index(pd.to_datetime(us_df['Year'], exact = False, forr
```

In [6]:

```python
us_df.drop(columns = 'Year', inplace = True)
us_df
```

Out[6]:

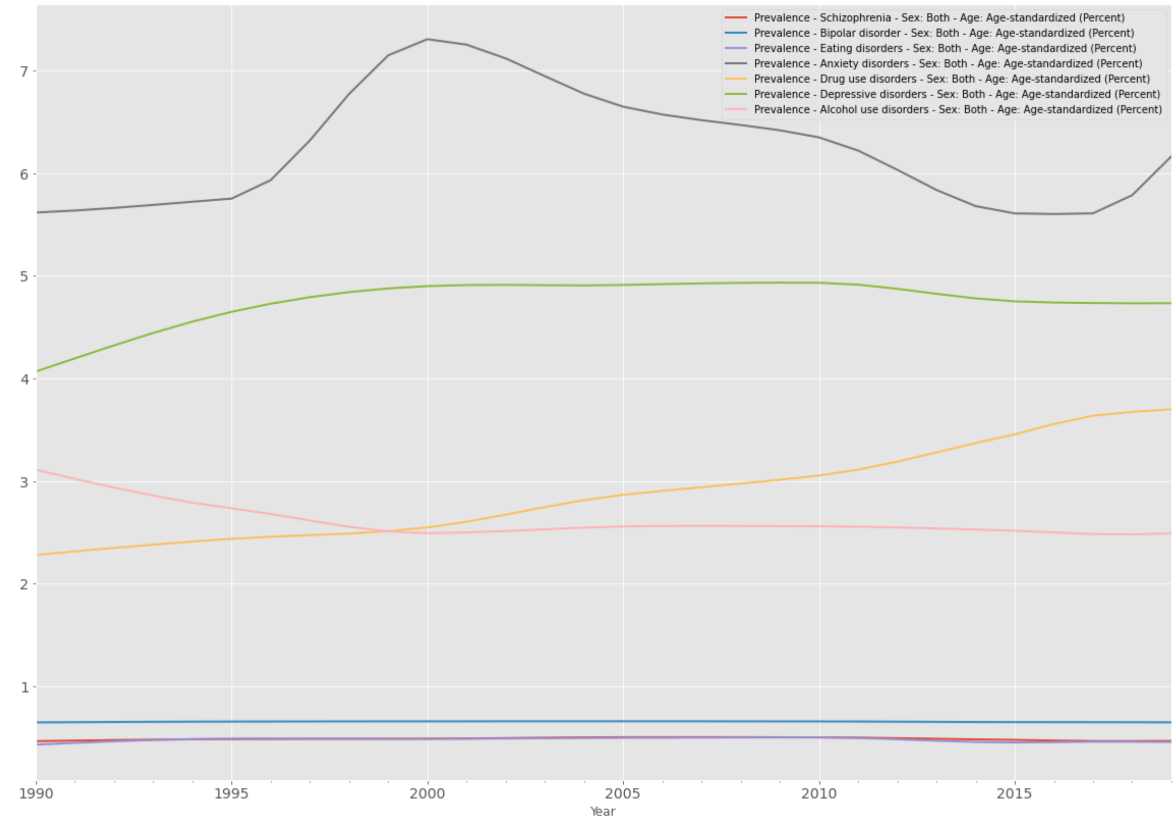
Year	Entity	Code	Prevalence - Schizophrenia - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Bipolar disorder - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Eating disorders - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Anxiety disorders - Sex: Both - Age: Age-standardized (Percent)	Prevalence Drug use disorders Sex: Both Age: Age standardizec (Percent
1990-01-01	United States	USA	0.467115	0.649644	0.433047	5.617003	2.281317
1991-01-01	United States	USA	0.472488	0.651606	0.450069	5.636548	2.316009
1992-01-01	United States	USA	0.477502	0.653518	0.465582	5.661951	2.349570
1993-01-01	United States	USA	0.481847	0.655238	0.478267	5.691142	2.381472

In [7]:

```python
#Graph the diseases to see if there are any obvious trends
us_df.plot(figsize=(20, 14), linewidth=2, fontsize=14)

```

Out[7]: <AxesSubplot:xlabel='Year'>



In [8]:

```python
#Rename the Depression Disorders column
us_df['Depression_Rates'] = us_df['Prevalence - Depressive disorders - Se
```

In [9]:

```
#Sanity Check
us_df
```

Out[9]:

	Entity	Code	Prevalence - Schizophrenia - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Bipolar disorder - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Eating disorders - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Anxiety disorders - Sex: Both - Age: Age-standardized (Percent)	Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent)	P... st...
Year								
1990-01-01	United States	USA	0.467115	0.649644	0.433047	5.617003	2.281317	
1991-01-01	United States	USA	0.472488	0.651606	0.450069	5.636548	2.316009	
1992-01-01	United States	USA	0.477502	0.653518	0.465582	5.661951	2.349570	
1993-01-01	United States	USA	0.481847	0.655238	0.478267	5.691142	2.381472	
1994-01-01	United States	USA	0.485216	0.656640	0.487285	5.722273	2.411349	
...	...	...	...	...	...	...	...	
2015-01-01	United States	USA	0.479682	0.652400	0.454035	5.608664	3.456076	
2016-01-01	United States	USA	0.473109	0.652017	0.457696	5.602520	3.556867	
2017-01-01	United States	USA	0.467995	0.651626	0.461926	5.609053	3.637681	
2018-01-01	United States	USA	0.467770	0.651148	0.461494	5.785829	3.674890	
2019-01-01	United States	USA	0.469107	0.650464	0.459038	6.163564	3.699504	

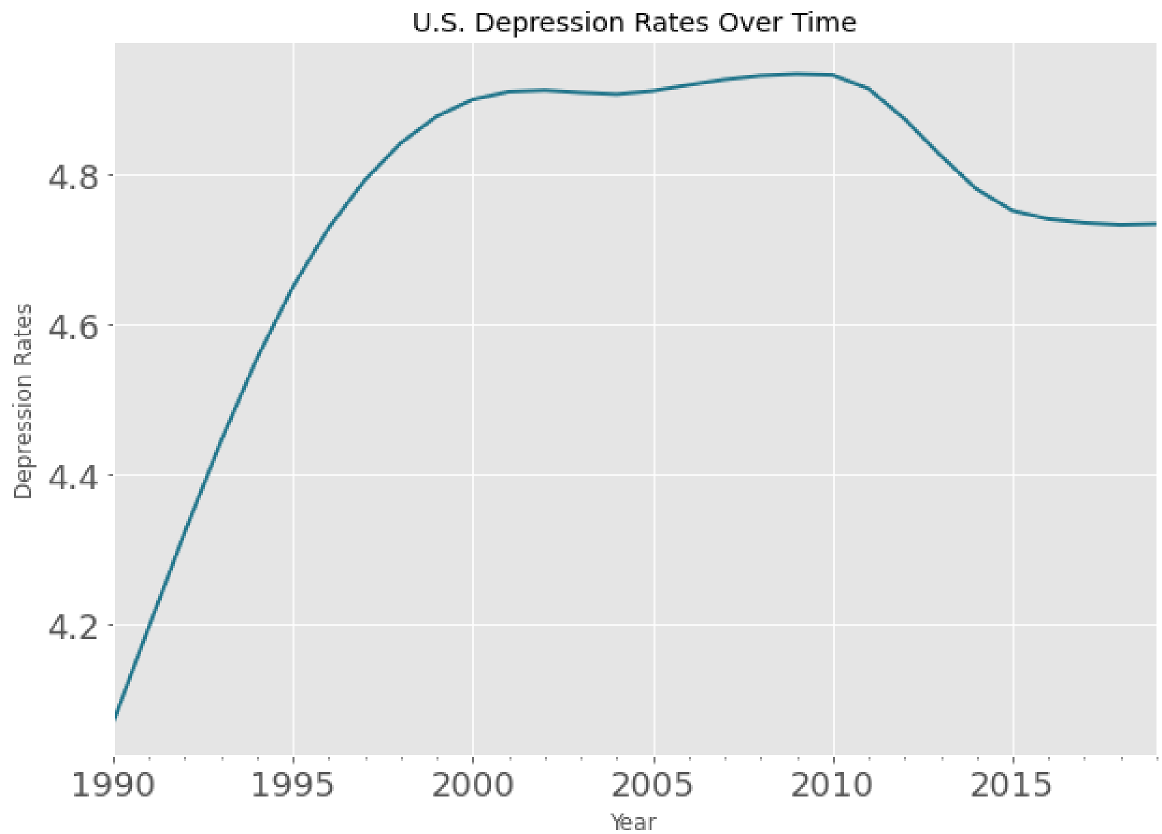
30 rows × 10 columns

In [10]:

```
#Graph Only the Depression Rate
us_depression_rates= us_df['Depression_Rates']
us_depression_rates.plot(figsize=(10, 7), linewidth=2, fontsize=18, xlab
                         , ylabel = "Depression Rates", title = "U.S. De
                         color = '#21758b',   )
```

Out[10]:

```
<AxesSubplot:title={'center':'U.S. Depression Rates Over Time'}, xlabel='Ye
ar', ylabel='Depression Rates'>
```



In [11]:

```
#Use a Dicky-Fuller Test to test for stationarity
dftest = adfuller(us_depression_rates)

#Make the output look better
dfoutput = pd.Series(
                dftest[0:4],
                index=['Test Statistic','p-value','#Lags Used','Number o
)

for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

display(dfoutput)
```

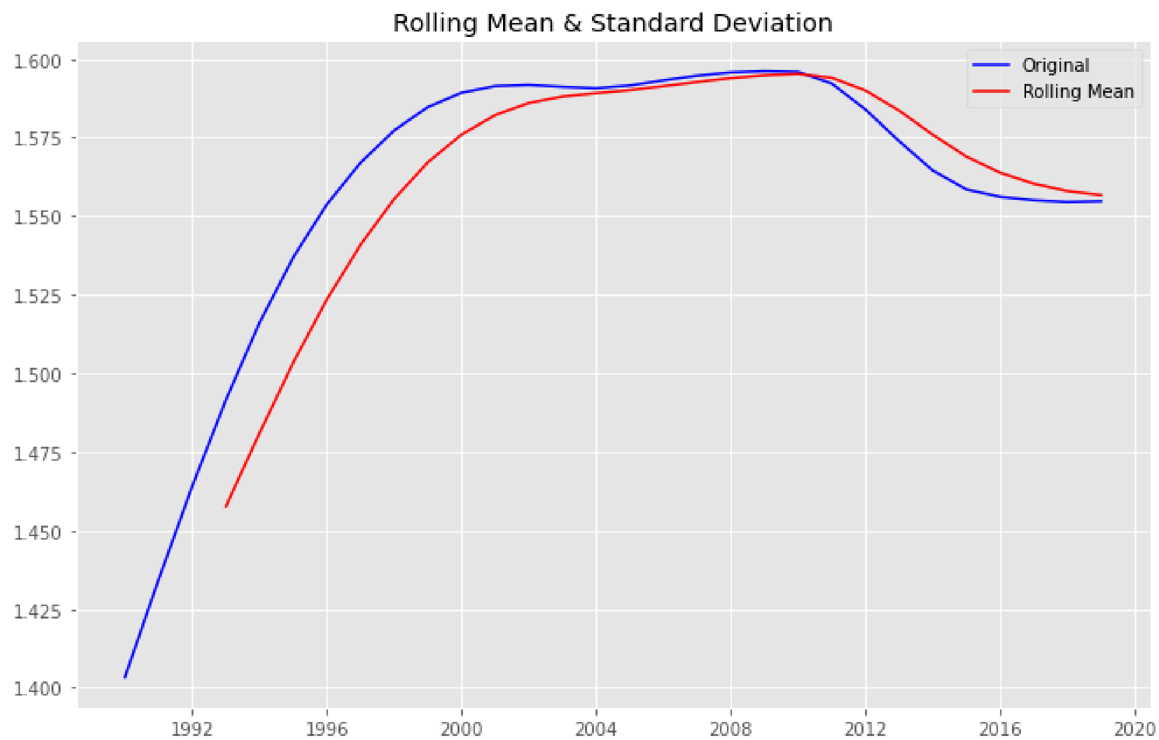
```
Test Statistic                  -1.613473
p-value                          0.476153
#Lags Used                       9.000000
Number of Observations Used     20.000000
Critical Value (1%)             -3.809209
Critical Value (5%)             -3.021645
Critical Value (10%)            -2.650713
dtype: float64
```

In [12]:

```
data_transform = pd.Series(np.log(us_depression_rates))
```

In [14]:

```
# Start with the square root transform to increase stationarity
data_transform = pd.Series(np.log(us_depression_rates))
#Subtract the rolling mean to increase stationarity
rolmean = data_transform.ewm(span = 4, min_periods = 4, adjust = False).ı
fig = plt.figure(figsize=(11, 7))
orig = plt.plot(data_transform, color='blue', label='Original')
mean = plt.plot(rolmean, color='red', label='Rolling Mean')
plt.legend(loc='best')
plt.title('Rolling Mean & Standard Deviation')
plt.show(block=False)
# Subtract the moving average from the original data and check head for ı
data_minus_rolmean = data_transform - rolmean
data_minus_rolmean
# Drop the NaN values from timeseries calculated above
# (the first few values didn't have a rolling mean)
data_minus_rolmean.dropna(inplace=True)
```



In [15]:

```
#Subtract the roling mean from above and drop null values
data_minus_rolmean = data_transform - rolmean
data_minus_rolmean
data_minus_rolmean.dropna(inplace=True)
```

In [16]:

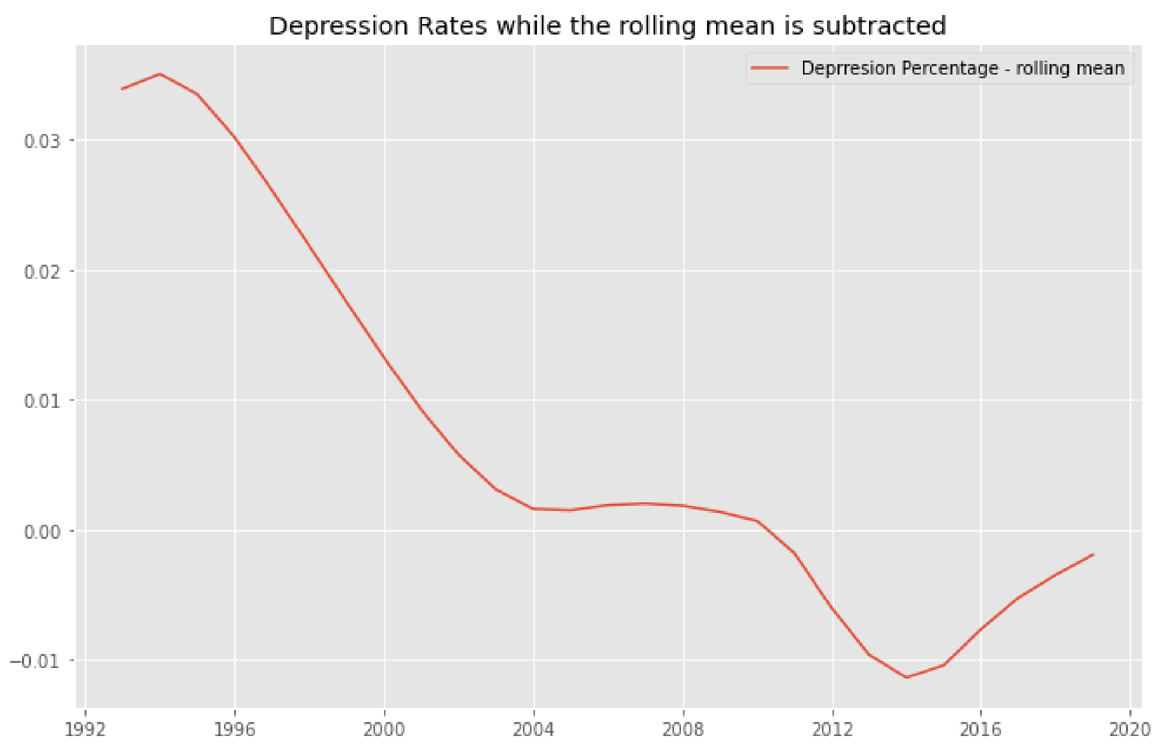
```
#Sanity Check
data_minus_rolmean
```

Out[16]:

```
Year
1993-01-01    0.033913
1994-01-01    0.035076
1995-01-01    0.033500
1996-01-01    0.030203
1997-01-01    0.026115
                ...
2015-01-01   -0.010458
2016-01-01   -0.007694
2017-01-01   -0.005265
2018-01-01   -0.003499
2019-01-01   -0.001949
Name: Depression_Rates, Length: 27, dtype: float64
```

In [17]:

```
#Plot the new data
fig = plt.figure(figsize=(11, 7))
plt.plot(data_minus_rolmean, label='Deprresion Percentage - rolling mean
plt.legend(loc='best')
plt.title('Depression Rates while the rolling mean is subtracted')
plt.show(block=False)
```



In [18]:

```
data_minus_rolmean
```

Out[18]:

```
Year
1993-01-01    0.033913
1994-01-01    0.035076
1995-01-01    0.033500
1996-01-01    0.030203
1997-01-01    0.026115
                ...
2015-01-01   -0.010458
2016-01-01   -0.007694
2017-01-01   -0.005265
2018-01-01   -0.003499
2019-01-01   -0.001949
Name: Depression_Rates, Length: 27, dtype: float64
```

In [19]:

```
#Use a Dicky-Fuller Test to test for stationarity
dftest = adfuller(data_minus_rolmean)

#Make the output look better
dfoutput = pd.Series(
                dftest[0:4],
                index=['Test Statistic','p-value','#Lags Used','Number o
)

for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

display(dfoutput)
```

```
Test Statistic                 -5.211491
p-value                         0.000008
#Lags Used                      9.000000
Number of Observations Used    17.000000
Critical Value (1%)            -3.889266
Critical Value (5%)            -3.054358
Critical Value (10%)           -2.666984
dtype: float64
```

In [24]:
```
#Use a Dicky-Fuller Test to test for stationarity
dftest = adfuller(data_transform)

#Make the output look better
dfoutput = pd.Series(
                dftest[0:4],
                index=['Test Statistic','p-value','#Lags Used','Number o
)

for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

display(dfoutput)
```

```
Test Statistic                 -1.734921
p-value                         0.413216
#Lags Used                      7.000000
Number of Observations Used    22.000000
Critical Value (1%)            -3.769733
Critical Value (5%)            -3.005426
Critical Value (10%)           -2.642501
dtype: float64
```

Ultimately the log transformed data was used for this analysis because ARIMA models does not require the data to be stationary. This will also allow us to easily transform the data back to it's original number for forecasting

Modeling

Train-Test Split

In [25]:
```
# find the index which allows us to split off 20% of the data
cutoff = round(data_transform.shape[0]*0.8)
cutoff
```

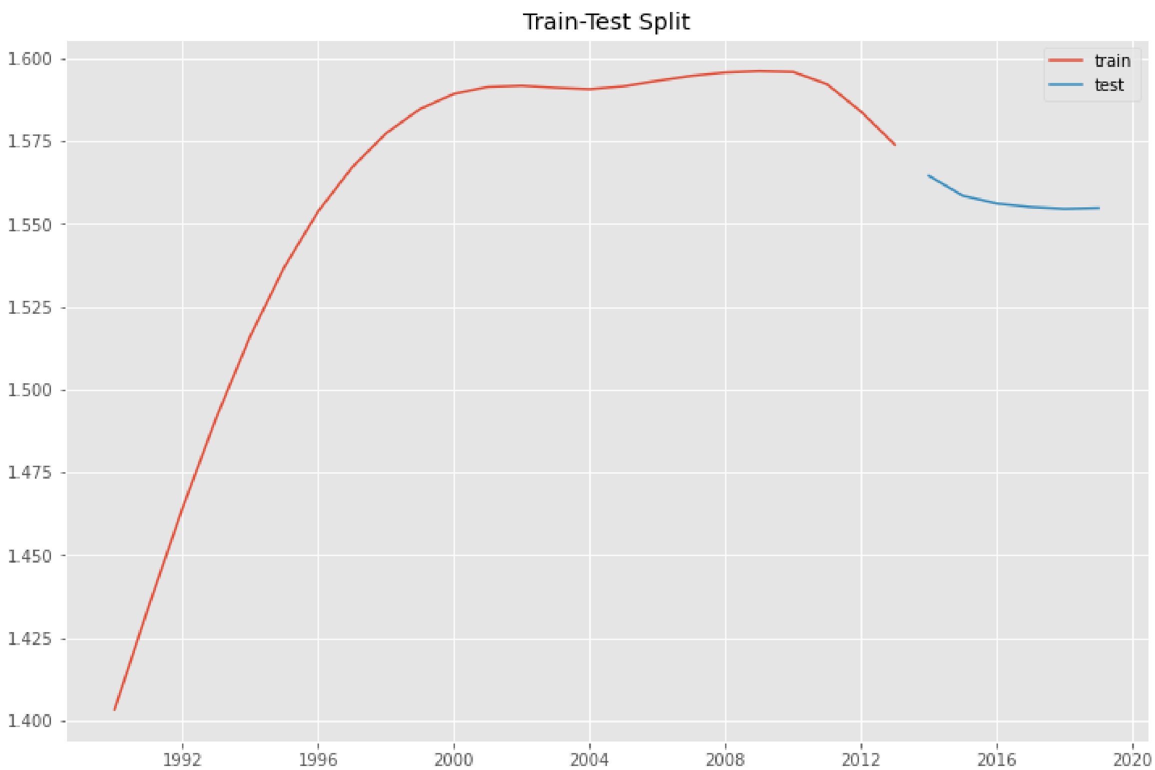
Out[25]: 24

In [26]:

```
# Define train and test sets according to the index found above
train = data_transform[:cutoff]

test = data_transform[cutoff:]

fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(train, label='train')
ax.plot(test, label='test')
ax.set_title('Train-Test Split');
plt.legend();
```



In [27]:

```python
# Seperate some of the data in the training set for validation purposes
split = TimeSeriesSplit()

for train_ind, val_ind in split.split(train):
    print(train_ind, val_ind)
```

```
[0 1 2 3] [4 5 6 7]
[0 1 2 3 4 5 6 7] [ 8  9 10 11]
[ 0  1  2  3  4  5  6  7  8  9 10 11] [12 13 14 15]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15] [16 17 18 19]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19] [20 21 22 23]
```

Baseline Model

Prediction is based solely on previous reporting cycle data. This will give us a good idea if our model has predictive capacity.

In [28]:

```python
naive = train.shift(1)
naive
```

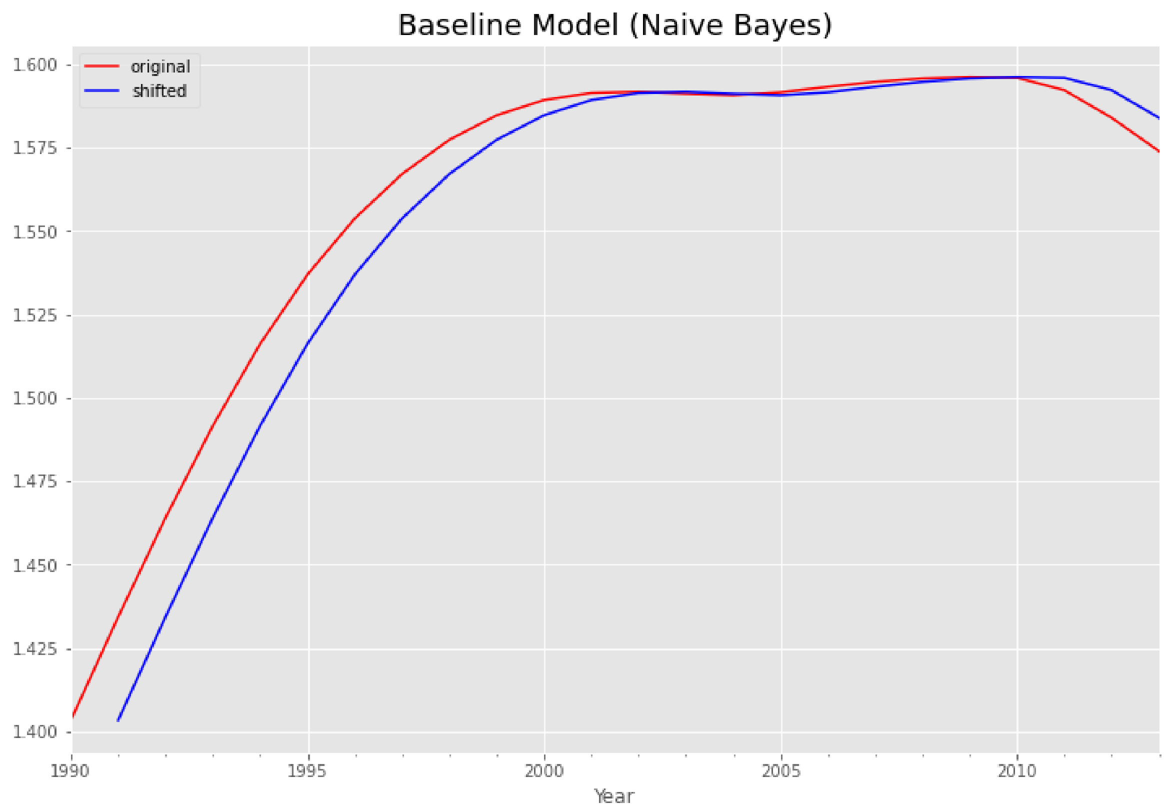
Out[28]:

```
Year
1990-01-01         NaN
1991-01-01    1.403322
1992-01-01    1.434277
1993-01-01    1.464001
1994-01-01    1.491545
                ...
2009-01-01    1.595675
2010-01-01    1.596109
2011-01-01    1.595853
2012-01-01    1.592155
2013-01-01    1.583896
Name: Depression_Rates, Length: 24, dtype: float64
```

In [104]:

```
#Visual Demonstration of naive model
fig, ax = plt.subplots(figsize = (12,8))

train[0:30].plot(ax=ax, c='r', label='original')
naive[0:30].plot(ax=ax, c='b', label='shifted')
ax.set_title('Baseline Model (Naive Bayes)', fontsize = 18)
ax.legend();
```



In [30]:

```
#Root Mean Squared Error for Baseline
np.sqrt(mean_squared_error(train[1:], naive.dropna()))
```

Out[30]: 0.013940508484064926

The baseline model RMSE is .014

Testing different ARIMA models to see which has the lowest AIC

In [107]:

```
ar_1 = ARIMA(train, order=(1, 1, 0)).fit()
ar_1.summary()
```

```
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
```

Out[107]:

SARIMAX Results

Dep. Variable:	Depression_Rates	**No. Observations:**	24
Model:	ARIMA(1, 1, 0)	**Log Likelihood**	98.115
Date:	Thu, 14 Jul 2022	**AIC**	-192.230
Time:	04:45:00	**BIC**	-189.959
Sample:	01-01-1990	**HQIC**	-191.659
	- 01-01-2013		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.9081	0.052	17.466	0.000	0.806	1.010
sigma2	1.073e-05	5.62e-06	1.908	0.056	-2.93e-07	2.18e-05

Ljung-Box (L1) (Q):	2.32	**Jarque-Bera (JB):**	135.10
Prob(Q):	0.13	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.24	**Skew:**	2.98
Prob(H) (two-sided):	0.06	**Kurtosis:**	13.27

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [108]:

```
ar_2 = ARIMA(train, order=(2, 1, 0)).fit()

print(ar_2.aic)
```

```
-229.51251381479508

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
```

In [109]:

```
ar_3 = ARIMA(train, order=(2, 1, 0)).fit()

print(ar_2.aic)
```

```
-229.51251381479508

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
```

In [37]:

```
ar_2 = ARIMA(train, order=(2, 2, 1)).fit()

print(ar_2.aic)
```

```
-219.42490949606915

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
```

In [110]:

```
ar_4 = ARIMA(train, order=(3, 2, 1)).fit()

print(ar_2.aic)
```

```
-229.51251381479508

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
```

In [111]:

```
ar_5 = ARIMA(train, order=(4, 2, 1)).fit()

print(ar_2.aic)
```

```
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\s
tatespace\sarimax.py:965: UserWarning: Non-stationary starting autoregressi
ve parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\s
tatespace\sarimax.py:977: UserWarning: Non-invertible starting MA parameter
s found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'


-229.51251381479508

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\base
\model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed t
o converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

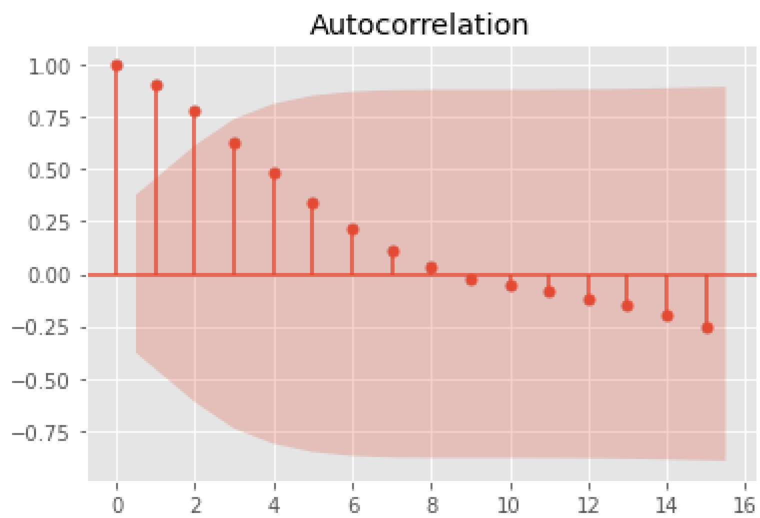
There does not seem to be a huge improvement using this method

Using ACF and PACF

A better way of going at this is by examining these charts. The ACF can tell us the optimal number of lags to go backwards and the PACF shows the direct effect of previous lags and thus the AR term for our model.

In [99]:

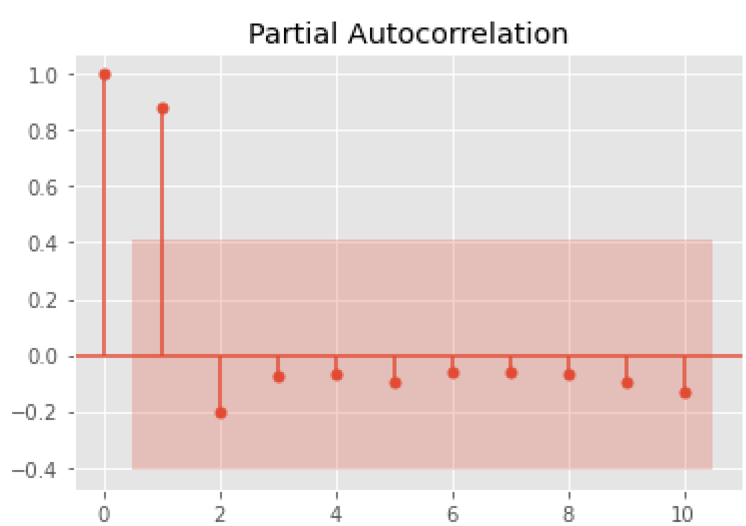
```
plot_acf(data_minus_rolmean);
```



It appears that an MA of around two or three will be best in the final model as those lags still have some predictive capabilities.

In [47]:

```
plot_pacf(train.diff().dropna(), lags = );
```



Analysis

The ACF seems to drop around three while the PACF seems to be best at 1. While working through some other models that are not in the notebook, I noticed a trend in the PACF that there was significant correlation every four years. This interested me because something important and potentially stressful happens every four years. Presidential elections can be a stressful thing for people who are worried about their security and the economy and potentially trigger depression.

For more research in this topic I suggest reading these articles (https://www.headspace.com/articles/election-anxiety (https://www.headspace.com/articles/election-anxiety), https://www.washingtonpost.com/lifestyle/wellness/stress-detox-election-anxiety/2020/11/09/96e5974c-1fa7-11eb-90dd-abd0f7086a91_story.html (https://www.washingtonpost.com/lifestyle/wellness/stress-detox-election-anxiety/2020/11/09/96e5974c-1fa7-11eb-90dd-abd0f7086a91_story.html))

As a result of this finding, I wanted to use a SARIMA model that could incorporate a seasonality component in the model.

Model Iteration

I used a function that would allow me to grid search through a bunch of different parameters in my SARIMAX model in order to find the best one. The models were evaluated by their Akaike information criterion (AIC). This allowed me to determine the best model for this dataset.

In [32]:

```
p = d = q = range(0, 2)
pdq = list(itertools.product(p, d, q))
seasonal_pdq = [(x[0], x[1], x[2],4) for x in list(itertools.product(p, 
print('Examples of parameter for SARIMA...')
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[1]))
print('SARIMAX: {} x {}'.format(pdq[1], seasonal_pdq[2]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[3]))
print('SARIMAX: {} x {}'.format(pdq[2], seasonal_pdq[4]))
```

```
Examples of parameter for SARIMA...
SARIMAX: (0, 0, 1) x (0, 0, 1, 4)
SARIMAX: (0, 0, 1) x (0, 1, 0, 4)
SARIMAX: (0, 1, 0) x (0, 1, 1, 4)
SARIMAX: (0, 1, 0) x (1, 0, 0, 4)
```

In [33]:

```
for param in pdq:
    for param_seasonal in seasonal_pdq:
        try:
            mod=SARIMAX(train,
                        order=param,
                        enforce_stationarity=False,
                        enforce_invertibility=False)
            results = mod.fit()
            print('ARIMA{}x{} - AIC:{}'.format(param,param_seasonal,resul
        except:
            print('Oops!')
            continue
```

```
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\ts
a\base\tsa_model.py:524: ValueWarning: No frequency information was prov
ided, so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\ts
a\base\tsa_model.py:524: ValueWarning: No frequency information was prov
ided, so inferred frequency AS-JAN will be used.
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ided, so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\ts
a\base\tsa_model.py:524: ValueWarning: No frequency information was prov
ided, so inferred frequency AS-JAN will be used.
```

Analysis

The best model I found was with an order of (2, 1, 1) and a seasonal order of (0, 0, 1, 4)

In [77]:

```python
#Cross validation for my training set before I apply it to the test set
#Reset the Index for easier validation
train_with_ind = train.reset_index()

for train_ind, val_ind in split.split(train_with_ind):
    sarimax = SARIMAX(endog=train_with_ind.iloc[train_ind, -1],
                      order=(2, 1, 1),
                     seasonal_order=(0, 0, 1, 4),
                     enforce_stationarity=False,
                     enforce_invertibility=False).fit()
    preds = sarimax.predict(typ='levels', start=val_ind[0], end=val_ind[
    true = train_with_ind.iloc[val_ind, -1]
    print(np.sqrt(mean_squared_error(true, preds)))
```

```
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\s
tatespace\sarimax.py:865: UserWarning: Too few observations to estimate sta
rting parameters for ARMA and trend. All parameters except for variances wi
ll be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\s
tatespace\sarimax.py:865: UserWarning: Too few observations to estimate sta
rting parameters for seasonal ARMA. All parameters except for variances wil
l be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\s
tatespace\sarimax.py:865: UserWarning: Too few observations to estimate sta
rting parameters for seasonal ARMA. All parameters except for variances wil
l be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\base
\model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed t
o converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "


0.05525329501129499
0.004856536739649589

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\s
tatespace\sarimax.py:865: UserWarning: Too few observations to estimate sta
rting parameters for seasonal ARMA. All parameters except for variances wil
l be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

0.0037555596738466294
0.000474664611816503
0.012926912557330056

C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\base
\model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed t
o converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

The cross validation scores look good and is ready to be applied to the test set. It should be noted that the model does best in the middle of the data set were there was less variation, and worse in the beginning and end when rates were rising fastest and dropping rapidly.

In [81]:

```python
#Create a variable for the final model
sari_mod = SARIMAX(train
                   ,order = (2, 1, 1)
                   ,seasonal_order = (0,0,1,4)
                   ,enforce_stationarity=False
                   ,enforce_invertibility=False).fit()

#Use the fitted model to predict on the test set
y_hat_test = sari_mod.predict(start=test.index[0], end=test.index[-1],ty
#Print the RMSE for our test data
np.sqrt(mean_squared_error(test, y_hat_test))
```

```
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
ase\tsa_model.py:524: ValueWarning: No frequency information was provided,
so inferred frequency AS-JAN will be used.
  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\tsa\b
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  warnings.warn('No frequency information was'
C:\Users\Johnn\anaconda3\envs\learn-env\lib\site-packages\statsmodels\base
\model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed t
o converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Out[81]:

```
0.0007408001705397787
```

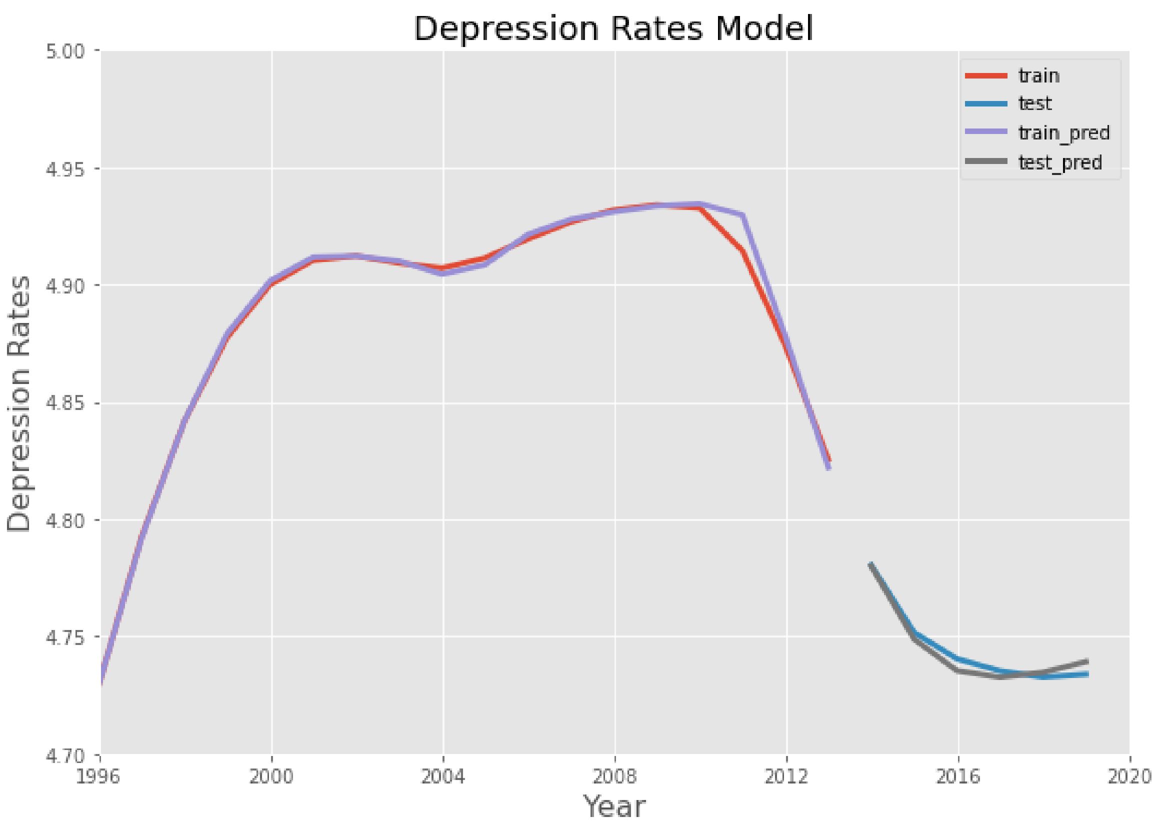
Analysis

The RMSE for this model was .0007 as compared to the baseline model which was .013. This is a significant improvement in error reduction by 95%.

Time Series Graphs

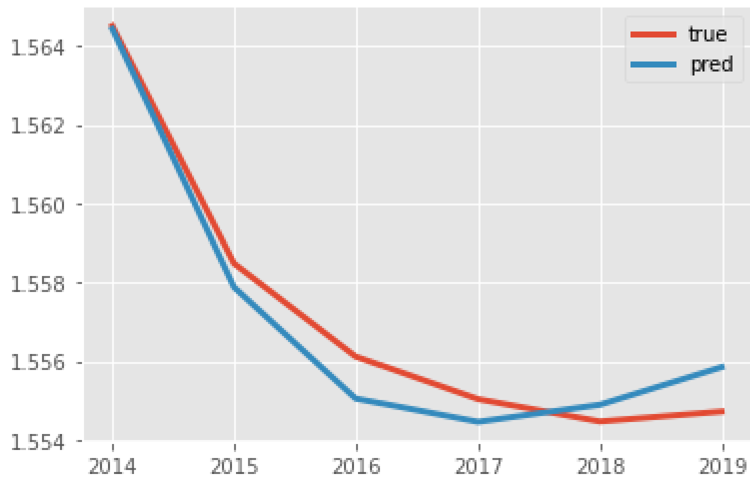
In [105]:

```
#Graphing the time series to get the full picture

#Defining variables for graph syntex
y_hat_train = sari_mod.predict(typ='levels')
y_hat_test = sari_mod.predict(start=test.index[0], end=test.index[-1],ty

fig, ax = plt.subplots(figsize = (10, 7))
#The data is un-transformed by exponentiating the values. This undoes the
ax.plot(np.exp(train), label='train', lw = 3)
ax.plot(np.exp(test), label='test', lw = 3)
ax.plot(np.exp(y_hat_train), label='train_pred', lw = 3)
ax.plot(np.exp(y_hat_test), label='test_pred', lw = 3)
ax.set_title ('Depression Rates Model', fontsize = 18)
ax.set_xlabel('Year', fontsize = 16)
ax.set_ylabel("Depression Rates", fontsize = 16)
plt.xlim(pd.Timestamp('1996-01-01'), pd.Timestamp('2020-01-01'))
plt.ylim(4.7, 5)
plt.legend();
```



In [89]:

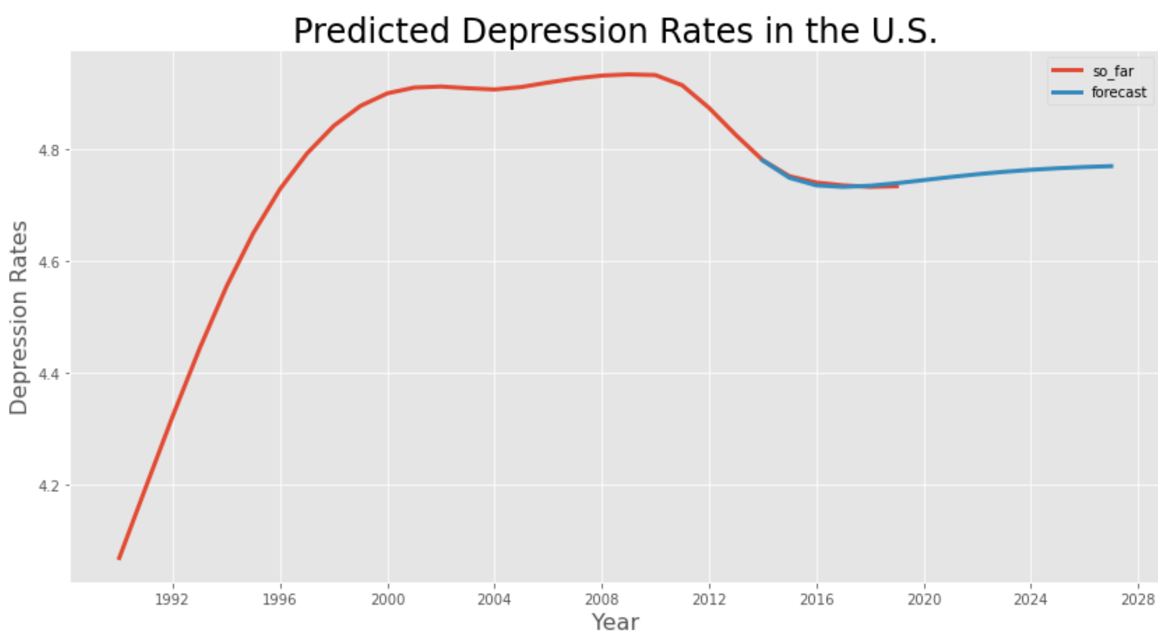
```
# Let's zoom in on test
fig, ax = plt.subplots()

ax.plot(test, label='true',lw = 3)
ax.plot(y_hat_test, label='pred', lw = 3)

plt.legend();
```



Forecasting Into the Futre

In [106]:

```
#Forecast out 8 years past the current dataset
forecast = sari_mod.forecast(steps=14)
fig, ax = plt.subplots(figsize = (14, 7))
ax.plot(us_depression_rates, label='so_far', lw = 3)
ax.plot(np.exp(forecast), label='forecast', lw = 3)
ax.set_title('Predicted Depression Rates in the U.S.', fontsize = 24)
ax.set_xlabel('Year', fontsize = 16)
ax.set_ylabel("Depression Rates", fontsize = 16)
plt.legend();
```



The model is predicting that rates will continue to grow for the foreseeable future.

This is important to the CDC because it shows that the prevalence of this disease is growing. This will allow them to better advocate for resources and expand outreach in order to curb it's spread.

Next Steps

In order to further assist the CDC, I would like to look at two more aspects of this dataset that could be useful to target outreach in communities that suffer from depression the most.

Although this data looked at the U.S. population as a whole, it is also broken down into gender and age. Depression in youth is growing faster (https://www.pewresearch.org/fact-tank/2019/07/12/a-growing-number-of-american-teenagers-particularly-girls-are-facing-depression/#:~:text=The%20total%20number%20of%20teenagers,than%20for%20boys%20(44%25 (https://www.pewresearch.org/fact-tank/2019/07/12/a-growing-number-of-american-teenagers-particularly-girls-are-facing-depression/#:~:text=The%20total%20number%20of%20teenagers,than%20for%20boys%20(44%25 and will have a bigger effect on those who suffer and the economy as a whole. This is due to higher lifetime treatment costs and lower economic potential.

Additionally, women are more likely to suffer from this disorder, and examining men and women separately may provide new insight into why.

Finally, other disorders are linked to depression so including drug abuse, anxiety disorders, may farther improve the model's accuracy.

In [ ]:

```
1
```