In [42]:
```
import pandas as pd
import statsmodels.api as sm
import warnings
warnings.filterwarnings('ignore')
```

1.) Import Data from FRED

In [2]:
```
data = pd.read_csv("TaylorRuleData.csv", index_col = 0)
```

In [3]:
```
data.index = pd.to_datetime(data.index)
```

In [28]:
```
data = data.dropna()
data
```

Out[28]:

	FedFunds	Unemployment	HousingStarts	Inflation
1959-01-01	2.48	6.0	1657.0	29.010
1959-02-01	2.43	5.9	1667.0	29.000
1959-03-01	2.80	5.6	1620.0	28.970
1959-04-01	2.96	5.2	1590.0	28.980
1959-05-01	2.90	5.1	1498.0	29.040
...	...	...	...	...
2023-07-01	5.12	3.5	1451.0	304.348
2023-08-01	5.33	3.8	1305.0	306.269
2023-09-01	5.33	3.8	1356.0	307.481
2023-10-01	5.33	3.8	1359.0	307.619
2023-11-01	5.33	3.7	1560.0	307.917

779 rows × 4 columns

2.) Do Not Randomize, split your data into Train, Test Holdout

In [21]:
```
split_1 = int(len(data)*.6)
split_2 = int(len(data)*.9)
data_in = data[:split_1]
data_out =  data[split_1:split_2]
data_hold = data[split_2:]
```

In [22]:
```
X_in =  data_in.iloc[:,1:]
y_in =  data_in.iloc[:,:1]
X_out = data_out.iloc[:,1:]
y_out = data_out.iloc[:,:1]
X_hold = data_hold.iloc[:,1:]
y_hold = data_hold.iloc[:,:1]
```

In [23]:
```
# Add Constants
X_in = sm.add_constant(X_in)
X_out =  sm.add_constant(X_out)
X_hold =  sm.add_constant(X_hold)
```

3.) Build a model that regresses FF~Unemp, HousingStarts, Inflation

In [24]:
```
model1 = sm.OLS(y_in,X_in).fit()
```

In [26]:
```
print(model1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               FedFunds   R-squared:                       0.088
Model:                            OLS   Adj. R-squared:                  0.082
Method:                 Least Squares   F-statistic:                     14.83
Date:                Wed, 10 Jan 2024   Prob (F-statistic):           3.09e-09
Time:                        16:18:21   Log-Likelihood:                -1202.0
No. Observations:                 467   AIC:                             2412.
Df Residuals:                     463   BIC:                             2429.
Df Model:                           3
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const             3.4750      0.985      3.529      0.000       1.540       5.410
Unemployment      0.5307      0.106      5.009      0.000       0.323       0.739
HousingStarts    -0.0005      0.000     -1.046      0.296      -0.001       0.000
Inflation         0.0077      0.004      2.173      0.030       0.001       0.015
==============================================================================
Omnibus:                       77.750   Durbin-Watson:                   0.043
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              122.849
Skew:                           1.039   Prob(JB):                     2.11e-27
Kurtosis:                       4.413   Cond. No.                     1.03e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.03e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [ ]:

```

```

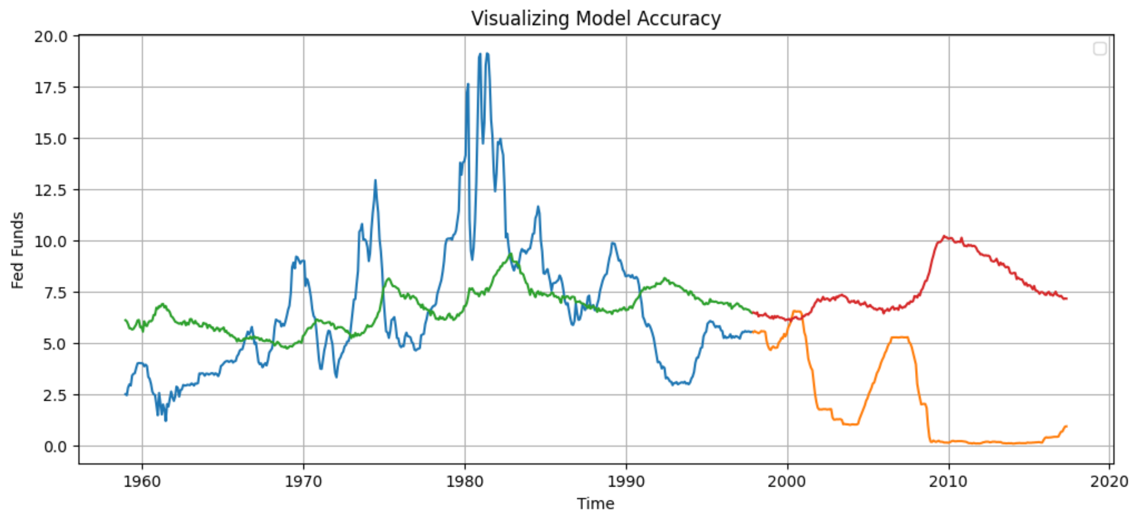
4.) Recreate the graph fro your model

In [30]:

```
import matplotlib.pyplot as plt
```

In [37]:

```
plt.figure(figsize = (12,5))

###
plt.plot(y_in)
plt.plot(y_out)
plt.plot(model1.predict(X_in))
plt.plot(model1.predict(X_out))
###

plt.ylabel("Fed Funds")
plt.xlabel("Time")
plt.title("Visualizing Model Accuracy")
plt.legend([])
plt.grid()
plt.show()
```



"All Models are wrong but some are useful" - 1976 George Box

5.) What are the in/out of sample MSEs

In [40]:

```
from sklearn.metrics import mean_squared_error
```

In [43]:

```
in_mse_1 = mean_squared_error(y_in,model1.predict(X_in))
out_mse_1 = mean_squared_error(y_out,model1.predict(X_out))
```

In [44]:
```
print("Insample MSE : ", in_mse_1)
print("Outsample MSE : ", out_mse_1)
```

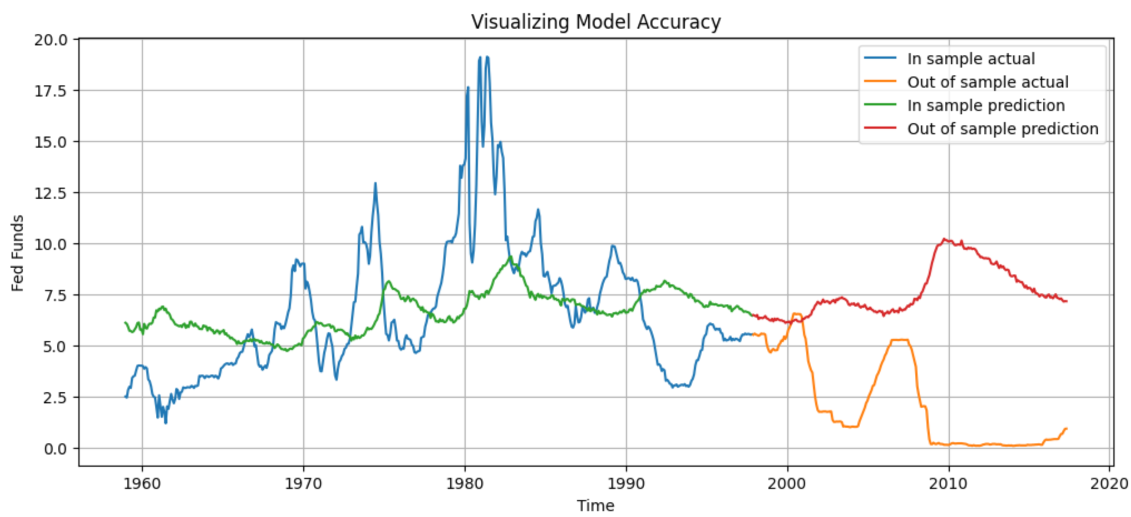
```
Insample MSE :  10.071422013168643
Outsample MSE :  40.36082783566727
```

6.) Using a for loop. Repeat 3,4,5 for polynomial degrees 1,2,3

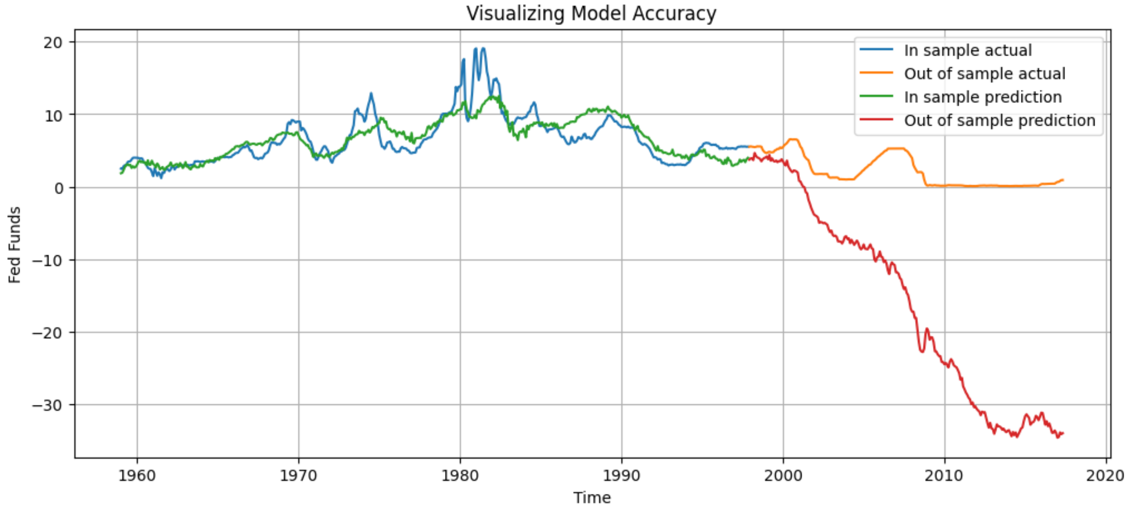
In [47]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [ ]:
```
poly = PolynomialFeatures(degree = degrees)
X_in_poly = poly.fit_transform(X_in)
X_out_poly = poly.transform(X_out)
```

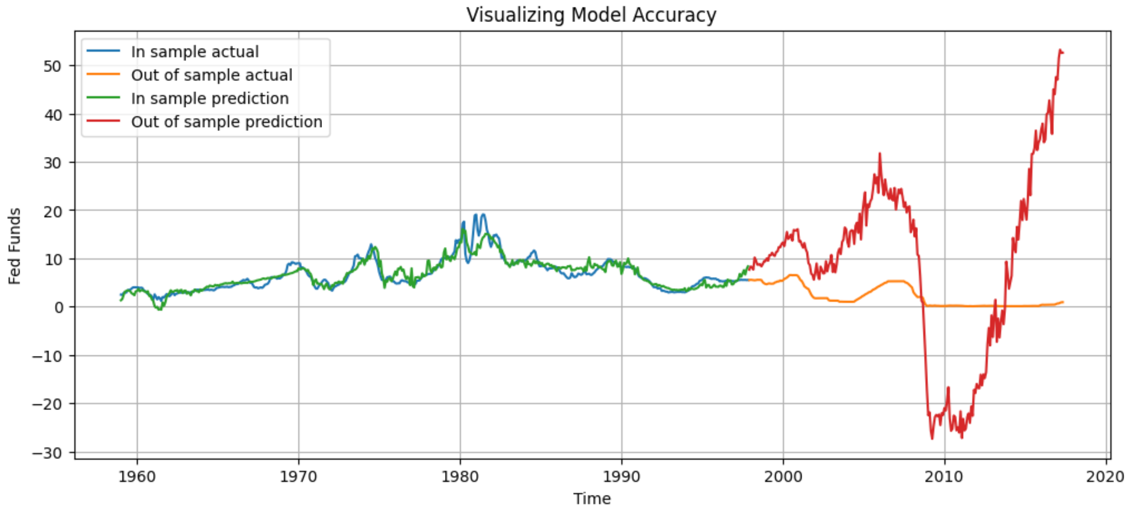
In [59]:
```
for degrees in range(1,4):
    poly = PolynomialFeatures(degree = degrees)
    X_in_poly = poly.fit_transform(X_in)
    X_out_poly = poly.transform(X_out)
    model = sm.OLS(y_in,X_in_poly).fit()
    plt.figure(figsize = (12,5))

    ###
    in_preds = model.predict(X_in_poly)
    in_preds=pd.DataFrame(in_preds,index = y_in.index)
    out_preds = model.predict(X_out_poly)
    out_preds=pd.DataFrame(out_preds,index = y_out.index)
    plt.plot(y_in)
    plt.plot(y_out)
    plt.plot(in_preds)
    plt.plot(out_preds)
    ###

    plt.ylabel("Fed Funds")
    plt.xlabel("Time")
    plt.title("Visualizing Model Accuracy")
    plt.legend(["In sample actual","Out of sample actual","In sample prediction", "O
    plt.grid()
    plt.show()
    in_mse_1 = mean_squared_error(y_in,model.predict(X_in_poly))
    out_mse_1 = mean_squared_error(y_out,model.predict(X_out_poly))
    print("Insample MSE : ", in_mse_1)
    print("Outsample MSE : ", out_mse_1)
```




```
Insample MSE :  10.07142201316864
Outsample MSE :  40.36082783566782
```




```
Insample MSE :  3.8634771392760685
Outsample MSE :  481.4465099294859
```




```
Insample MSE :  1.8723636266506438
Outsample MSE :  371.7680409381023
```

7.) State your observations :

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The more the complexity, the model is getting over fit and Outsample MSE is increasing.

In [ ]: