In [1]:
```
import pandas as pd
import statsmodels.api as sm
```

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 [4]:
```
data.dropna(inplace=True)
```

In [5]:
```
data.head()
```

Out[5]:

	FedFunds	Unemployment	HousingStarts	Inflation
1959-01-01	2.48	6.0	1657.0	29.01
1959-02-01	2.43	5.9	1667.0	29.00
1959-03-01	2.80	5.6	1620.0	28.97
1959-04-01	2.96	5.2	1590.0	28.98
1959-05-01	2.90	5.1	1498.0	29.04

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

In [7]:
```
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 [8]:
```
X_in = data_in.iloc[:,1:]
y_in = data_in.iloc[:,0]
X_out = data_out.iloc[:,1:]
y_out = data_out.iloc[:,0]
X_hold = data_hold.iloc[:,1:]
y_hold = data_hold.iloc[:,0]
```

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

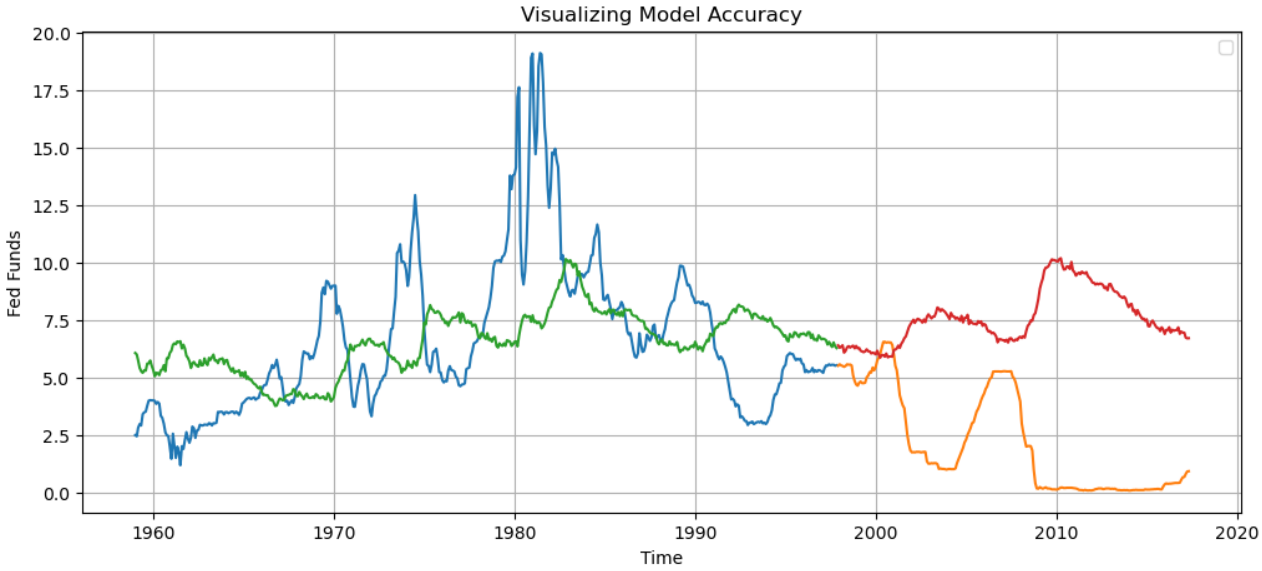
3.) Build a model that regresses FF~Unemp, HousingStarts, Inflation

In [9]:
```
model1 = sm.OLS(y_in,X_in).fit()
```

4.) Recreate the graph fro your model

In [11]:
```
import matplotlib.pyplot as plt
```

In [13]:
```
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 [14]:
```
from sklearn.metrics import mean_squared_error
```

In [16]:
```
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 [17]:
```
print("Insample MSE : ", in_mse_1)
print("Outsample MSE : ", out_mse_1)
```

```
Insample MSE :  10.342261026777946
Outsample MSE :  39.8622093480945
```

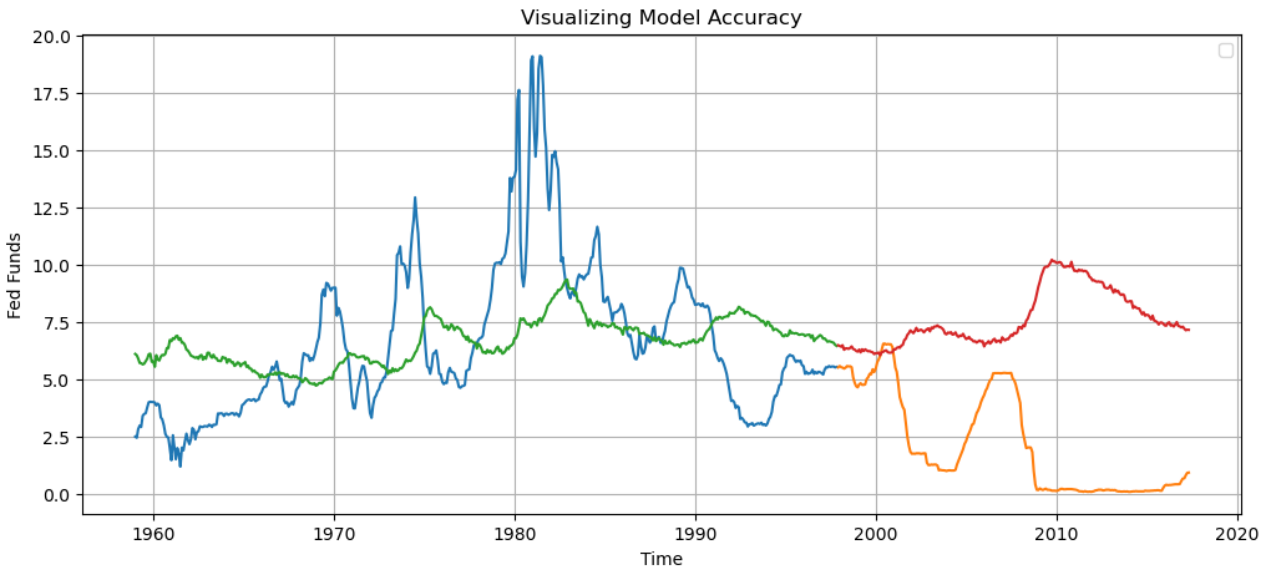
6.) Using a for loop. Repeat 3,4,5 for polynomial degrees 1,2,3

In [19]:
```
from sklearn.preprocessing import PolynomialFeatures
```

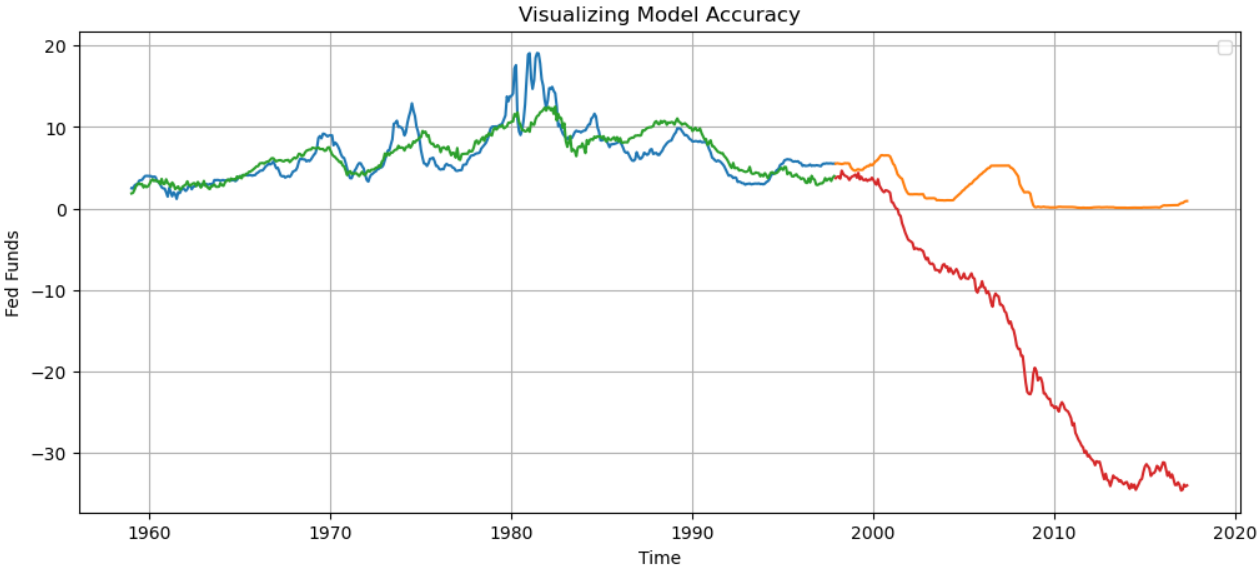
In [20]:
```
max_degrees=3
#we already did poly=1 now we do poly=2, x*2,x_1*x_2,x_2*2, poly=3,4..
```

In [22]:
```
for degrees in range(1,1+max_degrees):
    print("DEGREES: ",degrees)
    poly=PolynomialFeatures(degree=degrees)
    X_in_poly=poly.fit_transform(X_in)
    X_out_poly=poly.transform(X_out)

    #Q3
    model1=sm.OLS(y_in,X_in_poly).fit()

    #Q4 #before output is indexed while model1.predict(X_in_poly) output is
    plt.figure(figsize=(12,5))

    in_preds=model1.predict(X_in_poly)
    in_preds=pd.DataFrame(in_preds,index=y_in.index)
    out_preds=model1.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([])
    plt.grid()
    plt.show()
    #Q5
    in_mse_1 = mean_squared_error(y_in,in_preds)
    out_mse_1 = mean_squared_error(y_out,out_preds)
    print("Insample MSE : ", in_mse_1)
    print("Outsample MSE : ", out_mse_1)
```

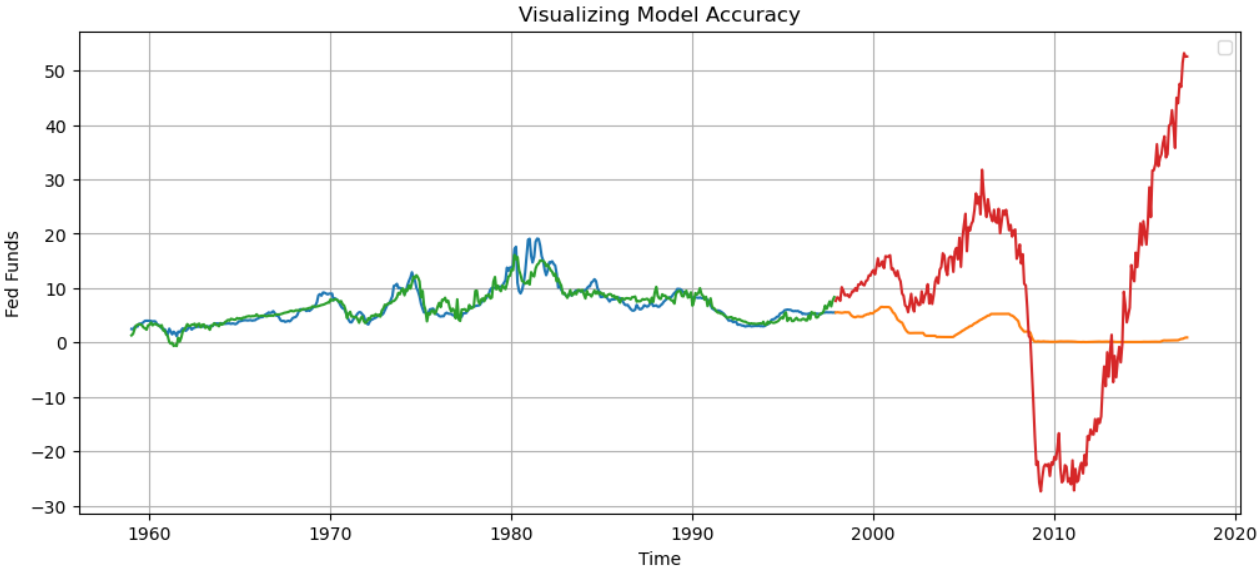
```
DEGREES:  1
```



```
Insample MSE :  10.071422013168641
Outsample MSE :  40.360827835668516
DEGREES:  2
```




```
Insample MSE :  3.863477139276067
Outsample MSE :  481.4465099449595
DEGREES:  3
```




```
Insample MSE :  1.8723636265932586
Outsample MSE :  371.768123590037
```

7.) State your observations :

In [23]:
```
#As the complexity of model increases(polynomial degree increases), the bias
#which is the insample MSE decreases.
#However, the variance of the model increases,
#where we can see the ratio of outsample MSE and insample MSE increases.
#the magnitude increases from 150(degree=2) to 370 (degree=3)
```

In [ ]:
```

```