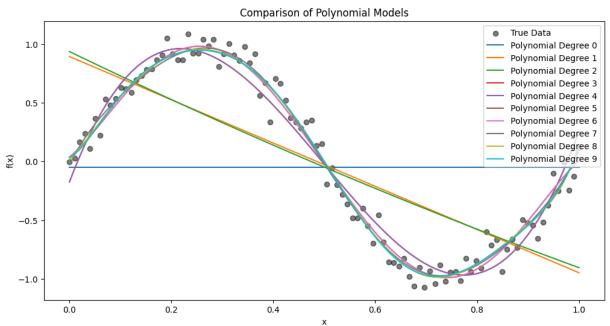
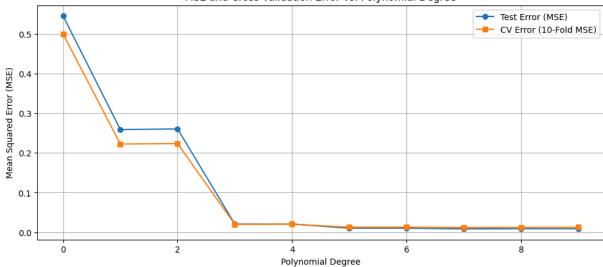
```
In [19]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
In [20]: # Generate synthetic dataset
X = np.linspace(0, 1, 100).reshape(-1, 1)
y = np.sin(2 * np.pi * X).ravel() + np.random.normal(0, 0.1, X.shape[0])
```

```
In [20]: # Generate synthetic dataset
         # Split into training and test sets (80/20)
         X train, X test, y train, y test = train test split(
             X, y, test size=0.2, random state=42
         X train, X test, y train, y test = train test split(
             X, y, test size=0.2,
         # Define polynomial degrees from 0 to 9
         degrees = list(range(10))
         models = \{\}
         test errors = {}
         cv errors = {}
         # Train models and compute errors
         for degree in degrees:
             model = make pipeline(PolynomialFeatures(degree), LinearRegression())
             model.fit(X train, y train)
             models[degree] = model
             test errors[degree] = np.mean((model.predict(X test) - y test) ** 2)
             cv errors[degree] = -np.mean(
                  cross val score(
                      model, X train, y train, scoring="neg mean squared error", cv=16
              )
         # Convert errors to DataFrame
         errors df = pd.DataFrame(
             {
                  "Degree": degrees,
                  "Test Error (MSE)": [test errors[d] for d in degrees],
                  "CV Error (10-Fold MSE)": [cv errors[d] for d in degrees],
             }
         # Plot polynomial models with predictions
         plt.figure(figsize=(12, 6))
         plt.scatter(X, y, label="True Data", color="black", alpha=0.5)
         X \text{ plot} = \text{np.linspace}(0, 1, 100).\text{reshape}(-1, 1)
         for degree in degrees:
             y pred = models[degree].predict(X plot)
```

```
plt.plot(X_plot, y_pred, label=f"Polynomial Degree {degree}")
plt.title("Comparison of Polynomial Models")
plt.xlabel("x")
plt.ylabel("f(x)")
plt.legend()
plt.show()
# Plot MSE per degree
plt.figure(figsize=(12, 5))
plt.plot(degrees, errors df["Test Error (MSE)"], marker="o", label="Test Err
plt.plot(
    degrees,
    errors df["CV Error (10-Fold MSE)"],
    marker="s",
    label="CV Error (10-Fold MSE)",
plt.xlabel("Polynomial Degree")
plt.ylabel("Mean Squared Error (MSE)")
plt.title("MSE and Cross-Validation Error vs. Polynomial Degree")
plt.legend()
plt.grid(True)
plt.show()
# Display errors
errors df = pd.DataFrame({
    "Degree": degrees,
    "Test Error (MSE)": [test errors[d] for d in degrees],
    "CV Error (10-Fold MSE)": [cv_errors[d] for d in degrees]
})
```



MSE and Cross-Validation Error vs. Polynomial Degree



In [21]: errors_df

	Degree	lest Liloi (MSL)	CV EITOI (10-FOId WISE)
0	0	0.544945	0.499397
1	1	0.258595	0.222255
2	2	0.260282	0.223326
3	3	0.020495	0.019815
4	4	0.020531	0.020367
5	5	0.010116	0.012578
6	6	0.010106	0.012752
7	7	0.008272	0.011877
8	8	0.008797	0.012227
9	9	0.008733	0.012510

```
In [22]: # Find the best degrees with the least errors
best_test_degree = errors_df.loc[errors_df["Test Error (MSE)"].idxmin(), "Defect best_cv_degree = errors_df.loc[errors_df["CV Error (10-Fold MSE)"].idxmin(), print(f"Best degree based on Test Error: {best_test_degree}")
print(f"Best degree based on CV Error: {best_cv_degree}")
```

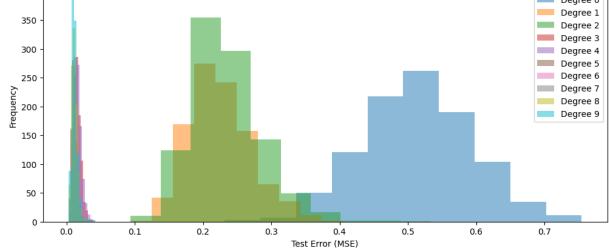
Best degree based on Test Error: 7 Best degree based on CV Error: 7

For Reproducibility, let's run the testing and cross validation several times

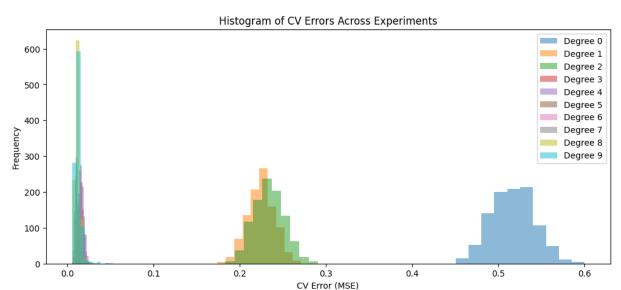
```
In [23]: # Define polynomial degrees from 0 to 9
num_experiments = 1000
test_errors_all = {degree: [] for degree in degrees}
cv_errors_all = {degree: [] for degree in degrees}
```

```
# Perform multiple evaluations
for _ in range(num_experiments):
   y = np.sin(2 * np.pi * X).ravel() + np.random.normal(0, 0.1, X.shape[0])
   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
    for degree in degrees:
        model = make pipeline(PolynomialFeatures(degree), LinearRegression()
        model.fit(X train, y train)
        test errors all[degree].append(np.mean((model.predict(X test) - y te
        cv errors all[degree].append(
            -np.mean(
                cross val score(
                    model, X train, y train, scoring="neg mean squared error
            )
        )
# Convert errors to DataFrame
errors df = pd.DataFrame(
    {
        "Degree": degrees,
        "Mean Test Error (MSE)": [np.mean(test errors all[d]) for d in degre
        "Mean CV Error (10-Fold MSE)": [np.mean(cv errors all[d]) for d in d
   }
)
# Plot histograms for errors per degree
plt.figure(figsize=(12, 5))
for degree in degrees:
    plt.hist(test errors all[degree], alpha=0.5, label=f"Degree {degree}")
plt.xlabel("Test Error (MSE)")
plt.ylabel("Frequency")
plt.title("Histogram of Test Errors Across Experiments")
plt.legend()
plt.show()
plt.figure(figsize=(12, 5))
for degree in degrees:
    plt.hist(cv errors all[degree], alpha=0.5, label=f"Degree {degree}")
plt.xlabel("CV Error (MSE)")
plt.ylabel("Frequency")
plt.title("Histogram of CV Errors Across Experiments")
plt.legend()
plt.show()
```





Histogram of Test Errors Across Experiments



Let's focus on smaller errors:

400

```
In [24]: # Plot histograms for errors per degree
         plt.figure(figsize=(12, 5))
         for degree in degrees:
             plt.hist(test errors all[degree], alpha=0.5, label=f"Degree {degree}")
         plt.xlabel("Test Error (MSE)")
         plt.xlim(0, 0.05)
         plt.ylabel("Frequency")
         plt.title("Histogram of Test Errors Across Experiments")
         plt.legend()
         plt.show()
         plt.figure(figsize=(12, 5))
         for degree in degrees:
             plt.hist(cv errors all[degree], alpha=0.5, label=f"Degree {degree}")
         plt.xlabel("CV Error (MSE)")
         plt.xlim(0, 0.05)
         plt.ylabel("Frequency")
         plt.title("Histogram of CV Errors Across Experiments")
```

