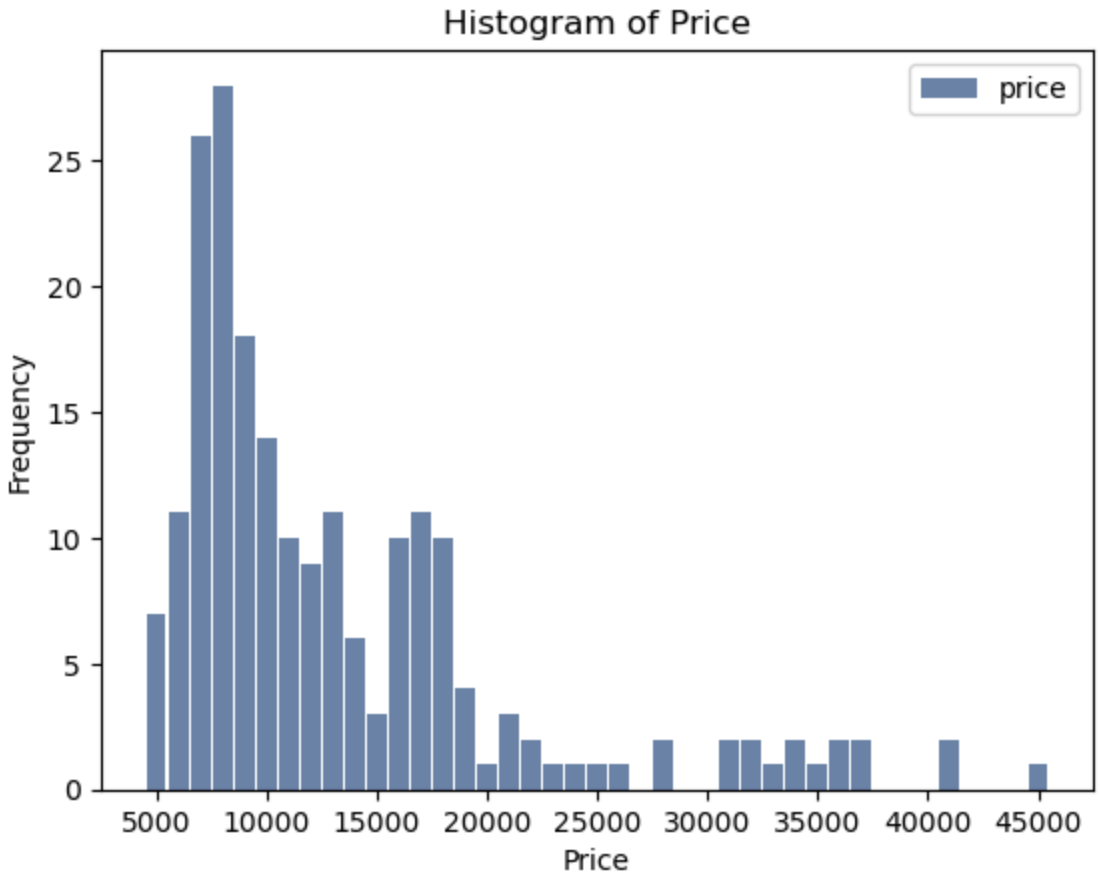
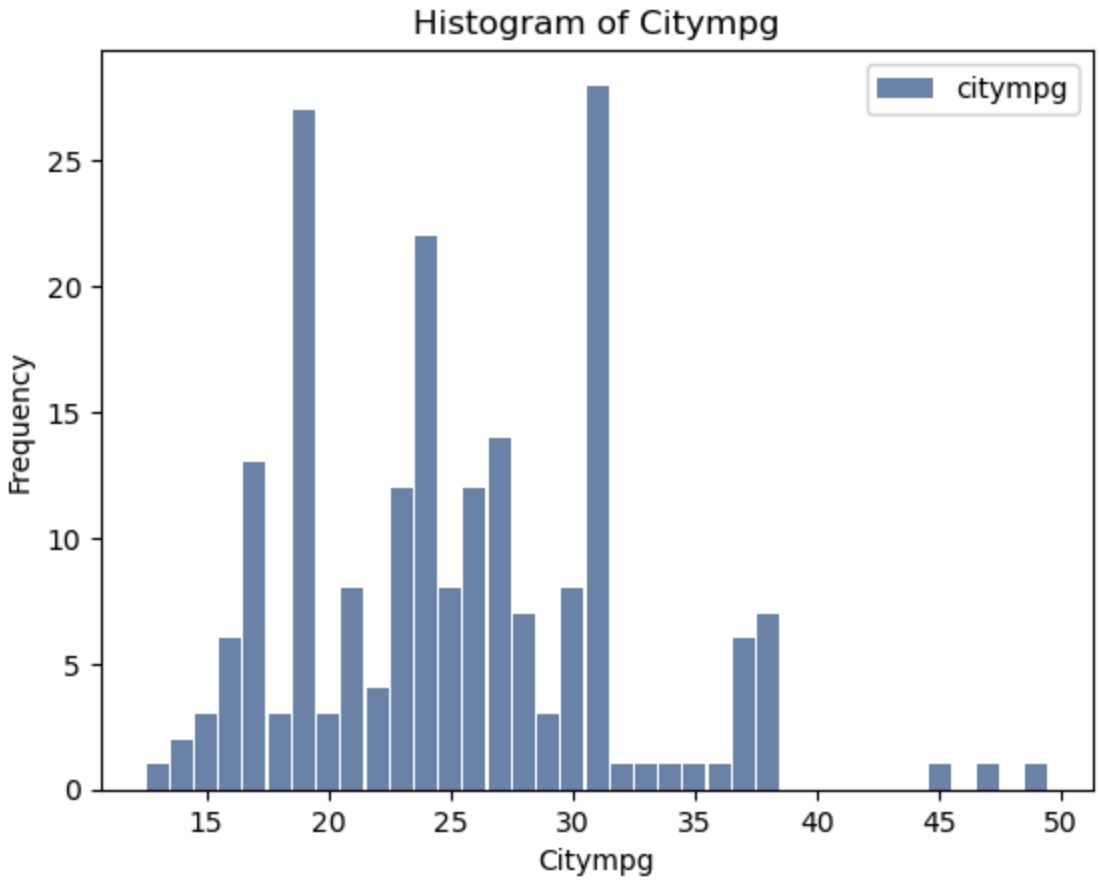
In [26]:
```
import pandas as pd
import thinkstats2
import thinkplot
import matplotlib.pyplot as plt
import numpy as np


# Download the dataset from Kaggle: https://www.kaggle.com/hellbuoy/car-price-prediction
# Save it in the same directory as your script/notebook

# Load the dataset into a Pandas DataFrame
data = pd.read_csv("CarPrice_Assignment.csv")

# Display the first few rows of the dataset
print(data.head())
```

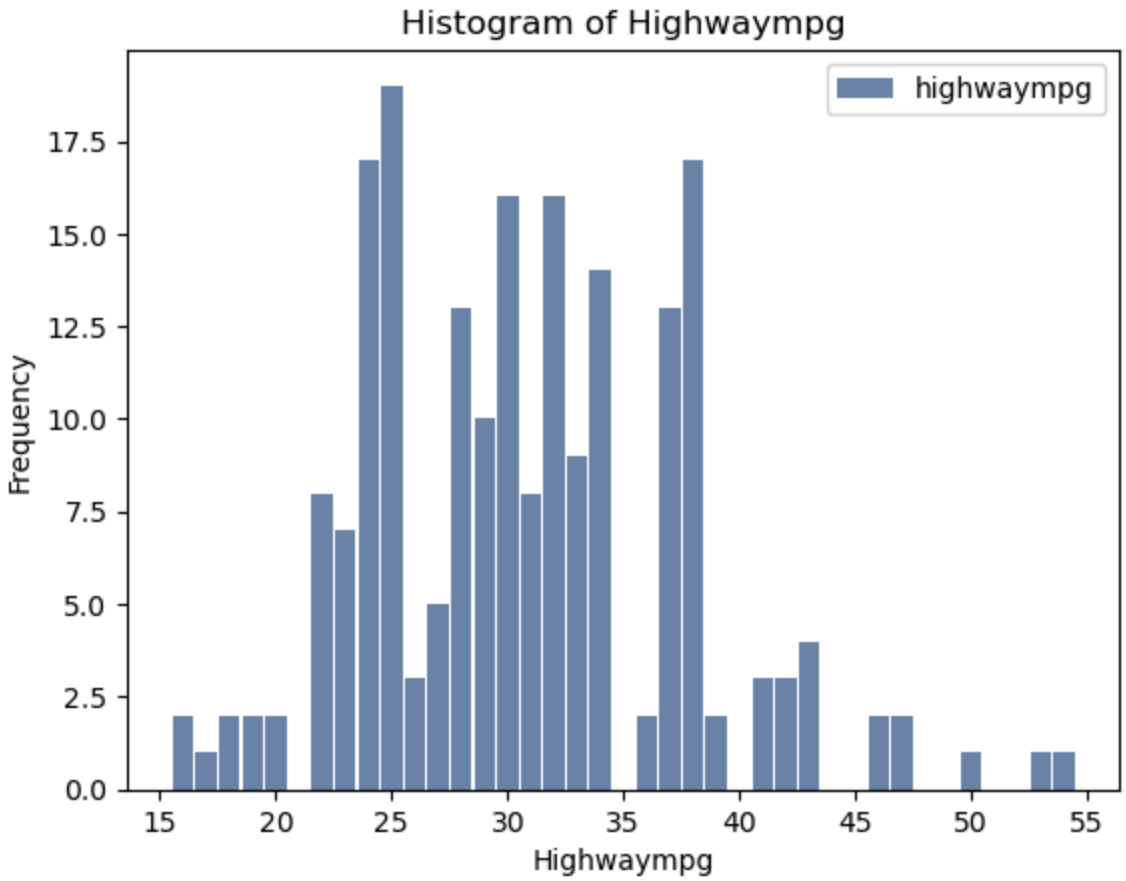
```
   car_ID  symboling                  CarName fueltype aspiration doornumber  \
0       1          3        alfa-romero giulia      gas        std        two
1       2          3       alfa-romero stelvio      gas        std        two
2       3          1  alfa-romero Quadrifoglio      gas        std        two
3       4          2               audi 100 ls      gas        std       four
4       5          2                audi 100ls      gas        std       four

       carbody drivewheel enginelocation  wheelbase  ...  enginesize  \
0  convertible        rwd          front       88.6  ...         130
1  convertible        rwd          front       88.6  ...         130
2    hatchback        rwd          front       94.5  ...         152
3        sedan        fwd          front       99.8  ...         109
4        sedan        4wd          front       99.4  ...         136

   fuelsystem  boreratio  stroke compressionratio horsepower  peakrpm citympg  \
0        mpfi       3.47    2.68              9.0        111     5000      21
1        mpfi       3.47    2.68              9.0        111     5000      21
2        mpfi       2.68    3.47              9.0        154     5000      19
3        mpfi       3.19    3.40             10.0        102     5500      24
4        mpfi       3.19    3.40              8.0        115     5500      18

   highwaympg    price
0          27  13495.0
1          27  16500.0
2          26  16500.0
3          30  13950.0
4          22  17450.0

[5 rows x 26 columns]
```

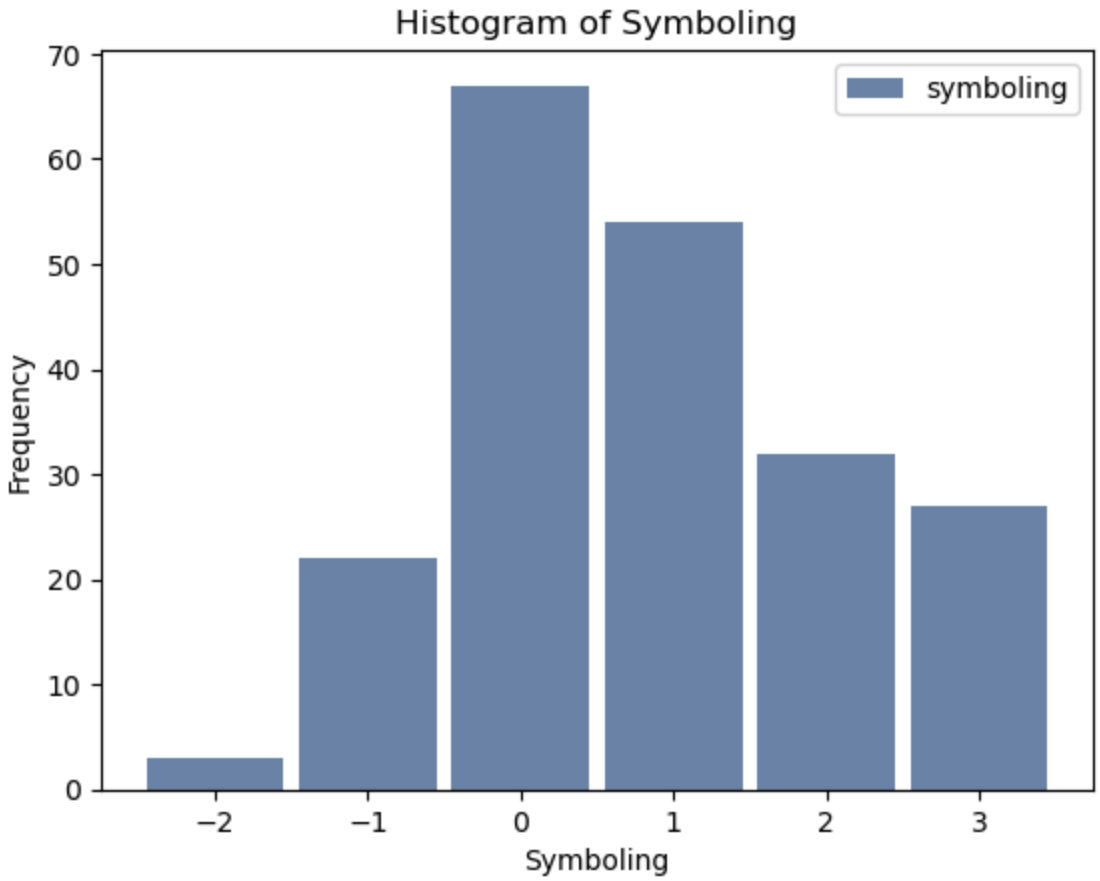
In [42]:

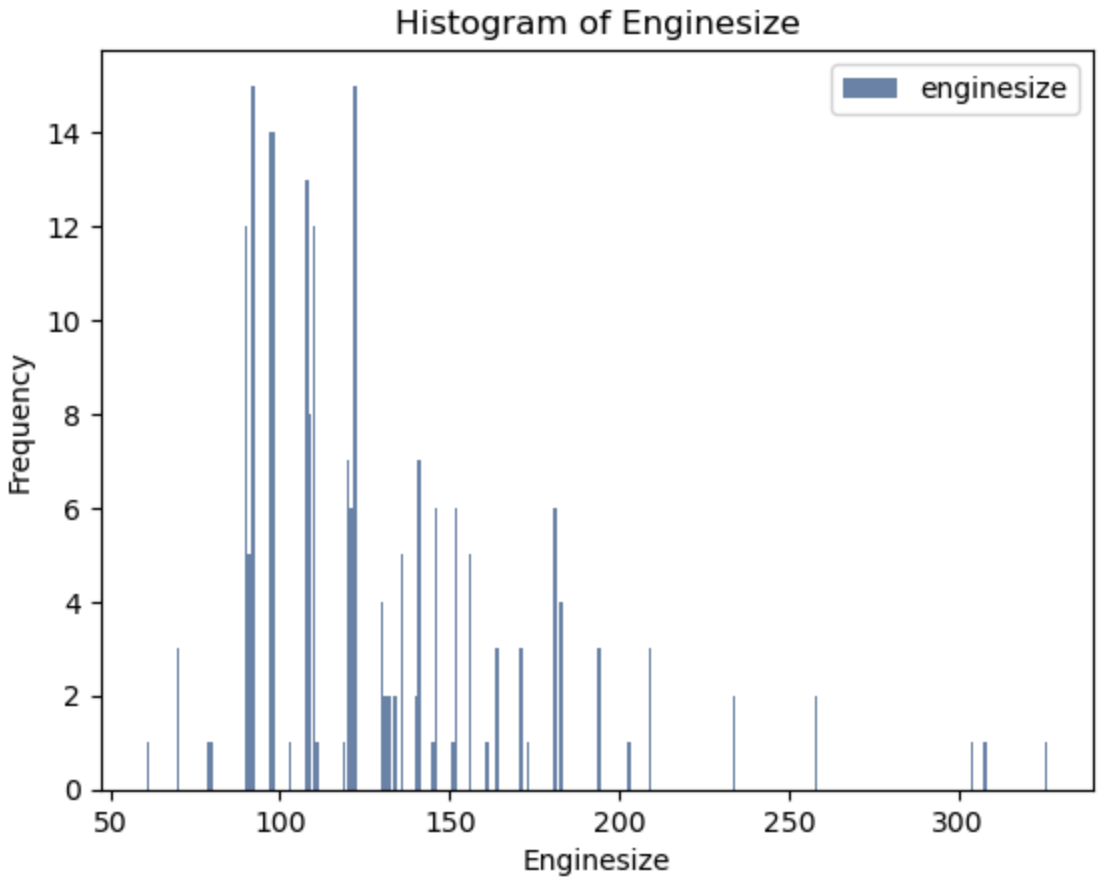
```
variables_of_interest = ['price', 'citympg', 'highwaympg', 'symboling', 'enginesize']
for variable in variables_of_interest:
    # Round price values to the nearest 1000
    if variable == 'price':
        data[variable] = round(data[variable] / 1000) * 1000

    # Histogram
    hist = thinkstats2.Hist(data[variable], label=variable)
    thinkplot.Hist(hist)
    thinkplot.Config(xlabel=variable.capitalize(), ylabel='Frequency', ytick_label_format='%.0fK')

    plt.title(f'Histogram of {variable.capitalize()}')
    plt.show()
```


Histogram of Price
price
Frequency
0
5
10
15
20
25
5000
10000
15000
20000
25000
30000
35000
40000
45000
Price


Histogram of Citympg
citympg
Frequency
Citympg
0
5
10
15
20
25
15
20
25
30
35
40
45
50


Histogram of Highwaympg
highwaympg
Frequency
Highwaympg
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
15
20
25
30
35
40
45
50
55


Histogram of Symboling
symboling
Frequency
Symboling
70
60
50
40
30
20
10
0
−2
−1
0
1
2
3



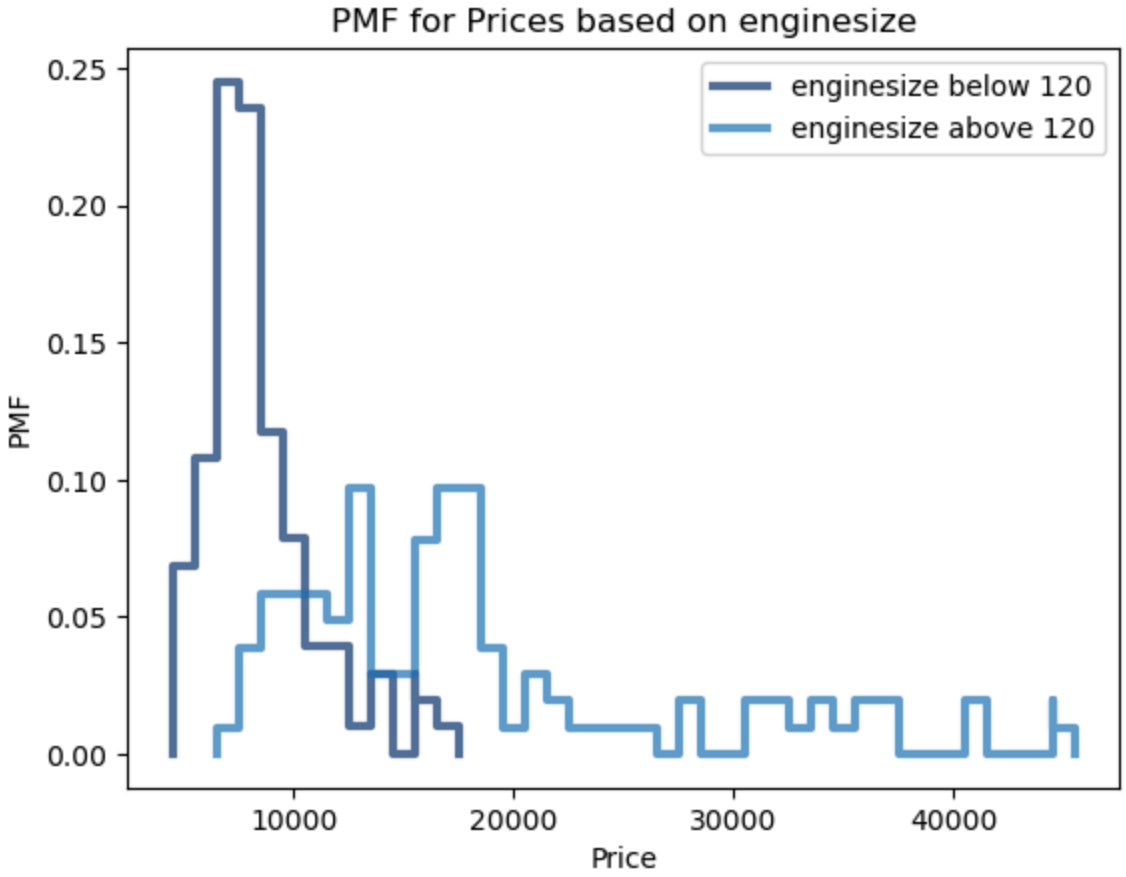
In [51]:
```
# Code for descriptive characteristics
for variable in variables_of_interest:
    mean = data[variable].mean()
    mode = data[variable].mode().values[0]
    spread = data[variable].std()
    median = data[variable].median()

    print(f"\nDescriptive Characteristics of {variable.capitalize()}:")
    print(f"Mean: {mean}\nMode: {mode}\nSpread: {spread}\nMedian: {median}\n")
```

```
Descriptive Characteristics of Price:
Mean: 13258.536585365853
Mode: 8000.0
Spread: 8005.910059895457
Median: 10000.0


Descriptive Characteristics of Citympg:
Mean: 25.21951219512195
Mode: 31
Spread: 6.54214165300162
Median: 24.0


Descriptive Characteristics of Highwaympg:
Mean: 30.75121951219512
Mode: 25
Spread: 6.88644313094182
Median: 30.0


Descriptive Characteristics of Symboling:
Mean: 0.8341463414634146
Mode: 0
Spread: 1.24530682810553
Median: 1.0


Descriptive Characteristics of Enginesize:
Mean: 126.90731707317073
Mode: 92
Spread: 41.642693438179826
Median: 120.0
```

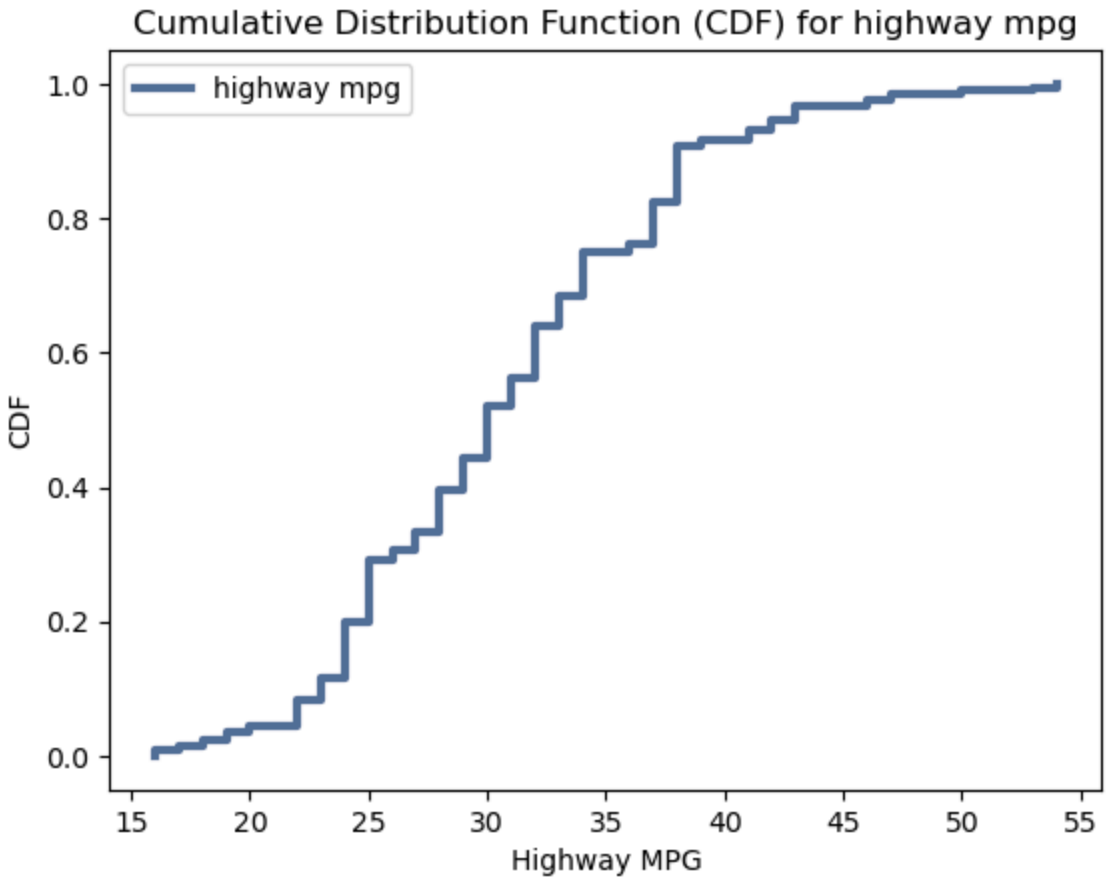
In [52]:

```
# Code for PMF comparison
scenario_1 = data[data['enginesize'] < 120]['price']
scenario_2 = data[data['enginesize'] >= 120]['price']

pmf_scenario_1 = thinkstats2.Pmf(scenario_1, label='enginesize below 120')
pmf_scenario_2 = thinkstats2.Pmf(scenario_2, label='enginesize above 120')

thinkplot.Pmfs([pmf_scenario_1, pmf_scenario_2])
thinkplot.Config(xlabel='Price', ylabel='PMF')
```

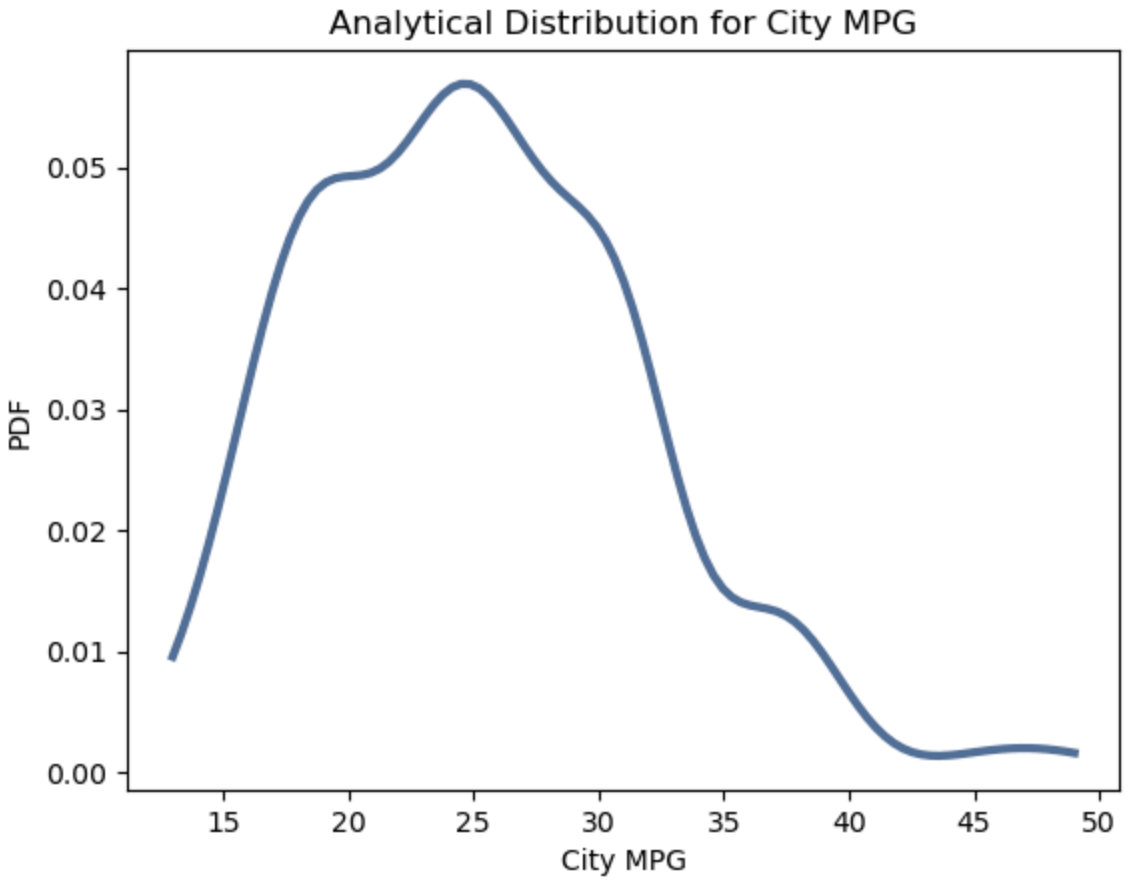
```
plt.title('PMF for Prices based on enginesize')
plt.show()
```



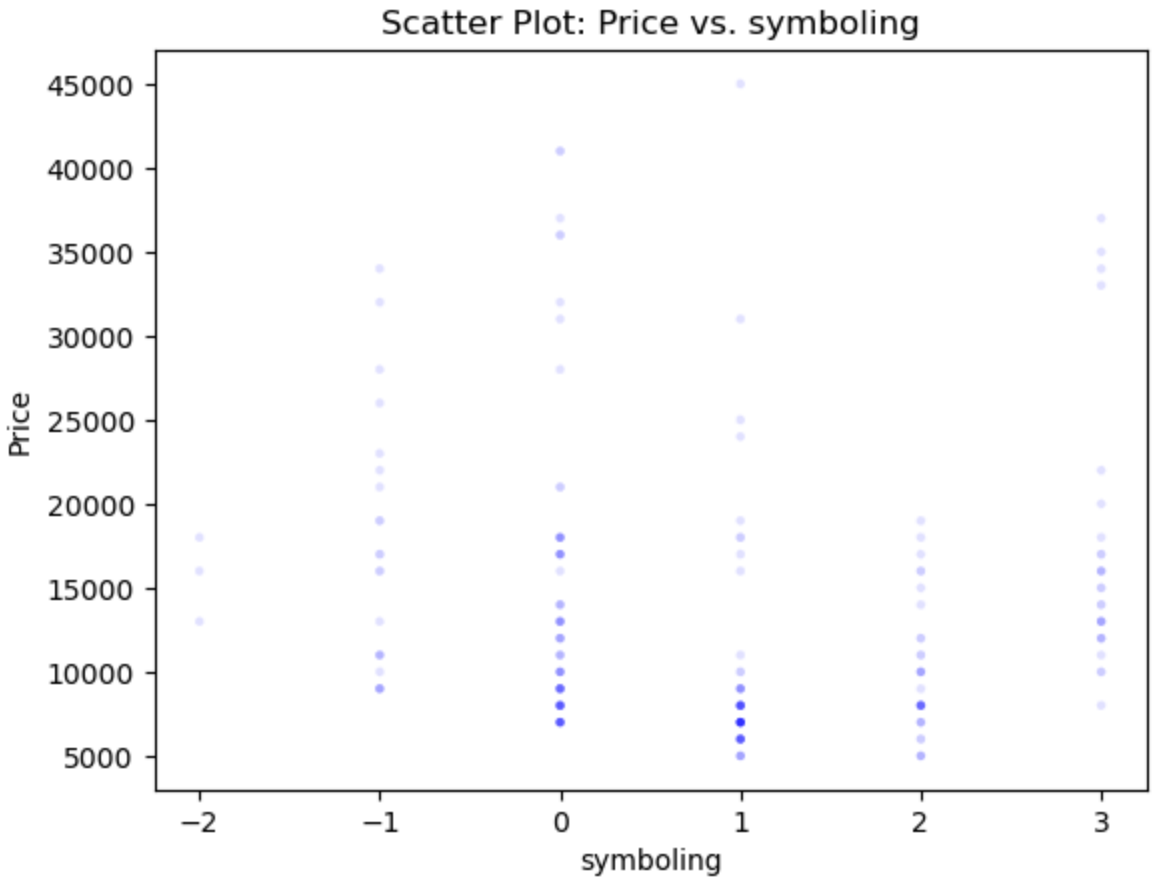
In [53]:
```
# Code for CDF
enginesize_cdf = thinkstats2.Cdf(data['highwaympg'], label='highway mpg')
thinkplot.Cdf(enginesize_cdf)
thinkplot.Config(xlabel='Highway MPG', ylabel='CDF')
plt.title('Cumulative Distribution Function (CDF) for highway mpg')
plt.show()
```

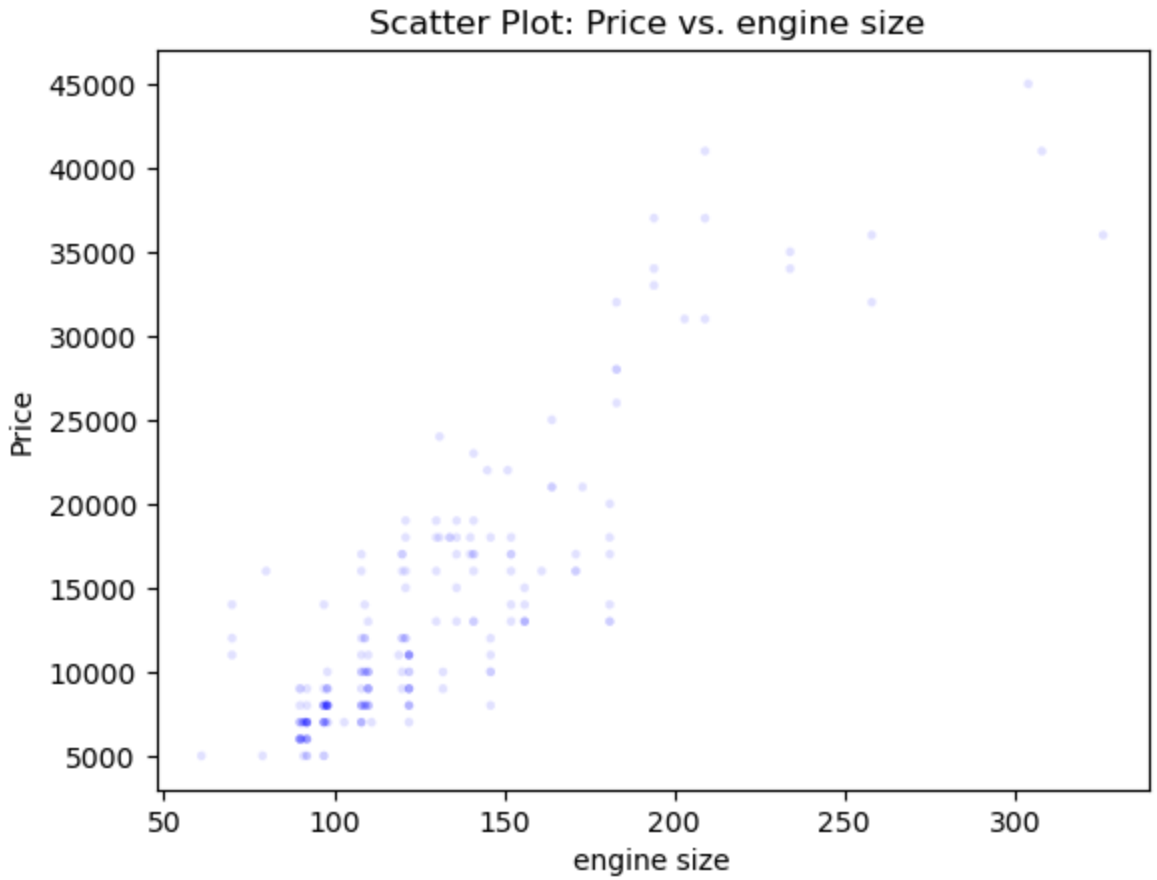


In [34]:
```
# Code for analytical distribution (e.g., CityMPG)
citympg_pdf = thinkstats2.EstimatedPdf(data['citympg'])
thinkplot.Pdf(citympg_pdf)
thinkplot.Config(xlabel='City MPG', ylabel='PDF')
plt.title('Analytical Distribution for City MPG')
plt.show()
```



In [55]:
```
# Code for scatter plots
# Assuming 'price' vs. 'citympg' and 'highwaympg' for illustration
thinkplot.Scatter(data['symboling'], data['price'], alpha=0.1, s=10)
thinkplot.Config(xlabel='symboling', ylabel='Price', title='Scatter Plot: Price vs. symboling')
plt.show()

thinkplot.Scatter(data['enginesize'], data['price'], alpha=0.1, s=10)
thinkplot.Config(xlabel='engine size', ylabel='Price', title='Scatter Plot: Price vs. engine size ')
plt.show()
```


Scatter Plot: Price vs. symboling
Price
45000
40000
35000
30000
25000
20000
15000
10000
5000
−2
−1
0
1
2
3
symboling



In [57]:
```
import pandas as pd
from scipy.stats import ttest_ind


# Hypothesis: Cars with higher mileage, low engine size will generally have lower prices.

# Define two groups based on the hypothesis
group_low = data[data['citympg'] > data['citympg'].median()]
group_high = data[data['citympg'] <= data['citympg'].median()]

# Perform t-test for citympg
t_stat, p_value = ttest_ind(group_low['price'], group_high['price'])

# Define significance level (alpha)
alpha = 0.05
```

```
# Print the results
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}")

# Compare p-value to the significance level
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference in prices between cars with high and low city r
else:
    print("Fail to reject the null hypothesis: There is no significant difference in prices between cars with high and l
```

```
T-statistic: -10.286158439804916
P-value: 3.0489665978885816e-20
Reject the null hypothesis: There is a significant difference in prices between cars with high and low city mileage.
```

In [58]:

```
import statsmodels.api as sm

# Code for regression analysis
X = data[['citympg', 'highwaympg', 'symboling', 'enginesize']]
X = sm.add_constant(X)  # Add a constant term
y = data['price']

model = sm.OLS(y, X).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.783
Model:                            OLS   Adj. R-squared:                  0.779
Method:                 Least Squares   F-statistic:                     180.5
Date:                Fri, 01 Mar 2024   Prob (F-statistic):           3.40e-65
Time:                        22:32:53   Log-Likelihood:                -1976.3
No. Observations:                 205   AIC:                             3963.
Df Residuals:                     200   BIC:                             3979.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1629.3368   2567.242      0.635      0.526   -3432.997    6691.671
citympg     -257.8838    177.297     -1.455      0.147    -607.496      91.728
highwaympg     6.7410    171.823      0.039      0.969    -332.076     345.558
symboling    -55.2696    222.870     -0.248      0.804    -494.746     384.207
enginesize   141.6129      8.663     16.347      0.000     124.531     158.695
==============================================================================
Omnibus:                       15.088   Durbin-Watson:                   0.822
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               21.400
Skew:                           0.472   Prob(JB):                     2.26e-05
Kurtosis:                       4.271   Cond. No.                     1.35e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.35e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```