In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import seaborn as sns
```

In [3]:
```
df = pd.read_csv("CarPrice_Assignment.csv")
```

In [4]:
```
x=df[['enginesize','horsepower','citympg','highwaympg']]
y=df['price']
```

In [5]:
```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [6]:
```
df = df.dropna()
```

In [7]:
```
print(df.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 [8]:
```
df
```

Out[8]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaymp
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5000	21	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5000	21	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0	154	5000	19	
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0	102	5500	24	
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0	115	5500	18	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
200	201	-1	volvo 145e (sw)	gas	std	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5	114	5400	23	
201	202	-1	volvo 144ea	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	8.7	160	5300	19	
202	203	-1	volvo 244dl	gas	std	four	sedan	rwd	front	109.1	...	173	mpfi	3.58	2.87	8.8	134	5500	18	
203	204	-1	volvo 246	diesel	turbo	four	sedan	rwd	front	109.1	...	145	idi	3.01	3.40	23.0	106	4800	26	
204	205	-1	volvo 264gl	gas	turbo	four	sedan	rwd	front	109.1	...	141	mpfi	3.78	3.15	9.5	114	5400	19	

205 rows × 26 columns

In [9]:
```
SS = StandardScaler()

x_trained = SS.fit_transform(X_train)
x_test = SS.fit_transform(X_test)
```

In [10]:
```
model = LinearRegression()
model.fit(x_trained, y_train)
```

Out[10]:
```
▾ LinearRegression
LinearRegression()
```

In [11]:
```
y_pred=model.predict(x_test)
```

In [12]:
```
print("-"*50)
print("MODEL COEFFICIENTS:")
for feature, coef in zip(x.columns, model.coef_):
    print(f"{feature:>12}: {coef:>10.2f}")
print(f"{'Intercept':>12}: {model.intercept_:>10.2f}")
```

```
--------------------------------------------------
MODEL COEFFICIENTS:
(feature:>12): (coef:>10.2f)
(feature:>12): (coef:>10.2f)
(feature:>12): (coef:>10.2f)
(feature:>12): (coef:>10.2f)
('Intercept':>12): (model.intercept_:>10.2f)
```

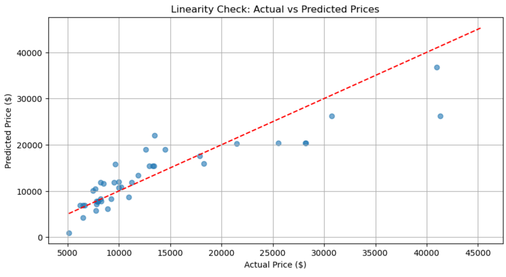
In [13]:
```
import numpy as np
from sklearn.metrics import mean_squared_error, r2_score

print("\nMODEL PERFORMANCE:")

print(f"{'MSE':>12}: {mean_squared_error(y_test, y_pred):>10.2f}")
print(f"{'RMSE':>12}: {np.sqrt(mean_squared_error(y_test, y_pred)):>10.2f}")
print(f"{'R-squared':>12}: {r2_score(y_test, y_pred):>10.2f}")

print("=" * 58)
```

```
MODEL PERFORMANCE:
         MSE: 17133687.82
        RMSE:    4139.29
   R-squared:       0.78
==========================================================
```

In [14]:
```
mse=mean_squared_error(y_test,y_pred)
print('Mean Squared Error=',mse)
rmse=np.sqrt(mse)
print("Root Mean Squared Error=",rmse)
r2score=r2_score(y_test,y_pred)
print('r2 score=',r2score)
```

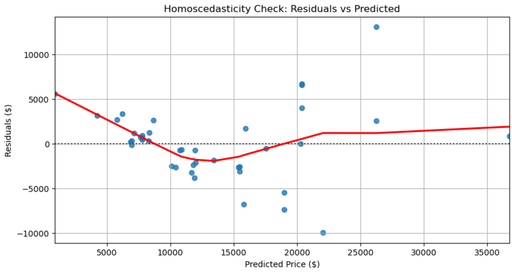
```
Mean Squared Error= 17133687.822608914
Root Mean Squared Error= 4139.285907328572
r2 score= 0.7829640847819556
```

In [15]:
```
plt.figure(figsize=(10, 5))
plt.scatter(y_test, y_pred, alpha=0.6)
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'r--')
plt.title("Linearity Check: Actual vs Predicted Prices")
plt.xlabel("Actual Price ($)")
plt.ylabel("Predicted Price ($)")
plt.grid(True)
plt.show()
```

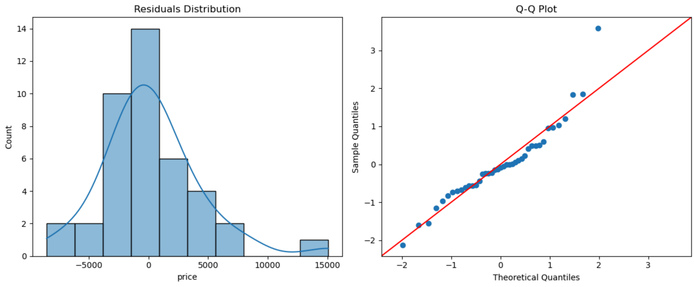


In [20]:
```
#2.Independence (Durbin-Watson)
import statsmodels.api as sm
residuals = y_test - y_pred
dw_test = sm.stats.durbin_watson(residuals)
print(f"\nDurbin-Watson Statistic: {dw_test:.2f}",
"\n(Values close to 2 indicate no autocorrelation)")

# 3. Homoscedasticity
plt.figure(figsize=(10, 5))
sns.residplot(x=y_pred, y=residuals, lowess=True, line_kws={'color': 'red'})
plt.title("Homoscedasticity Check: Residuals vs Predicted")
plt.xlabel("Predicted Price ($)")
plt.ylabel("Residuals ($)")
plt.grid(True)
plt.show()
```

```
Durbin-Watson Statistic: 2.34
(Values close to 2 indicate no autocorrelation)
```



In [21]:
```
#4. Normality of residuals
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12,5))
sns.histplot(residuals, kde=True, ax=ax1)
ax1.set_title("Residuals Distribution")
sm.qqplot(residuals, line='45', fit=True, ax=ax2)
ax2.set_title("Q-Q Plot")
plt.tight_layout()
plt.show()
```



In [ ]:
```
```

In [ ]:
```
```