In [69]:
```
import pandas as pd
raw_data = pd.read_csv('datasets/carPrice.csv')
raw_data.describe(include='all')
```

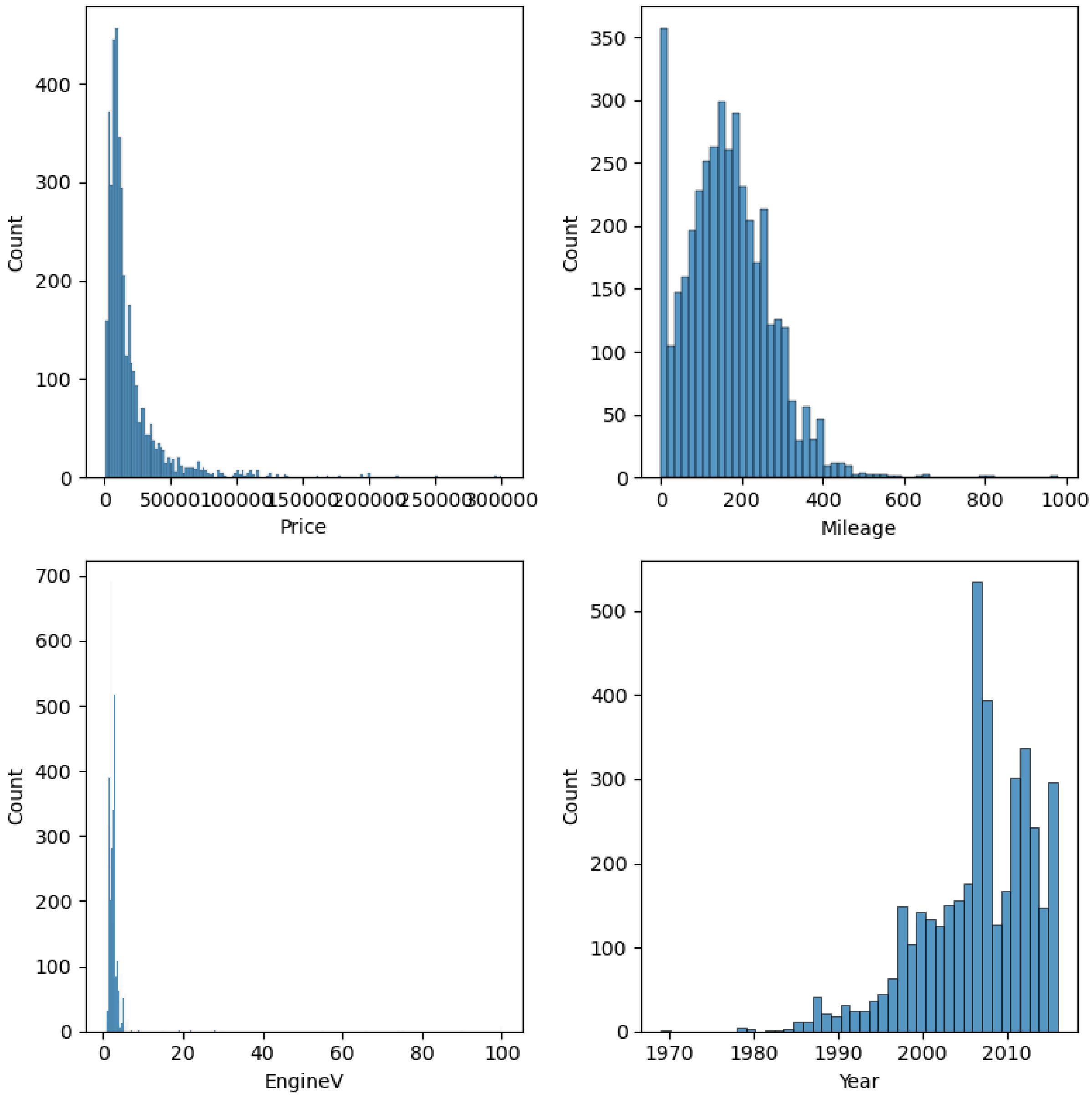
Out[69]:

	Brand	Price	Body	Mileage	EngineV	Engine Type	Regist
count	4345	4173.000000	4345	4345.000000	4195.000000	4345	
unique	7	NaN	6	NaN	NaN	4	
top	Volkswagen	NaN	sedan	NaN	NaN	Diesel	
freq	936	NaN	1649	NaN	NaN	2019	
mean	NaN	19418.746935	NaN	161.237284	2.790734	NaN	
std	NaN	25584.242620	NaN	105.705797	5.066437	NaN	
min	NaN	600.000000	NaN	0.000000	0.600000	NaN	
25%	NaN	6999.000000	NaN	86.000000	1.800000	NaN	
50%	NaN	11500.000000	NaN	155.000000	2.200000	NaN	
75%	NaN	21700.000000	NaN	230.000000	3.000000	NaN	
max	NaN	300000.000000	NaN	980.000000	99.990000	NaN	

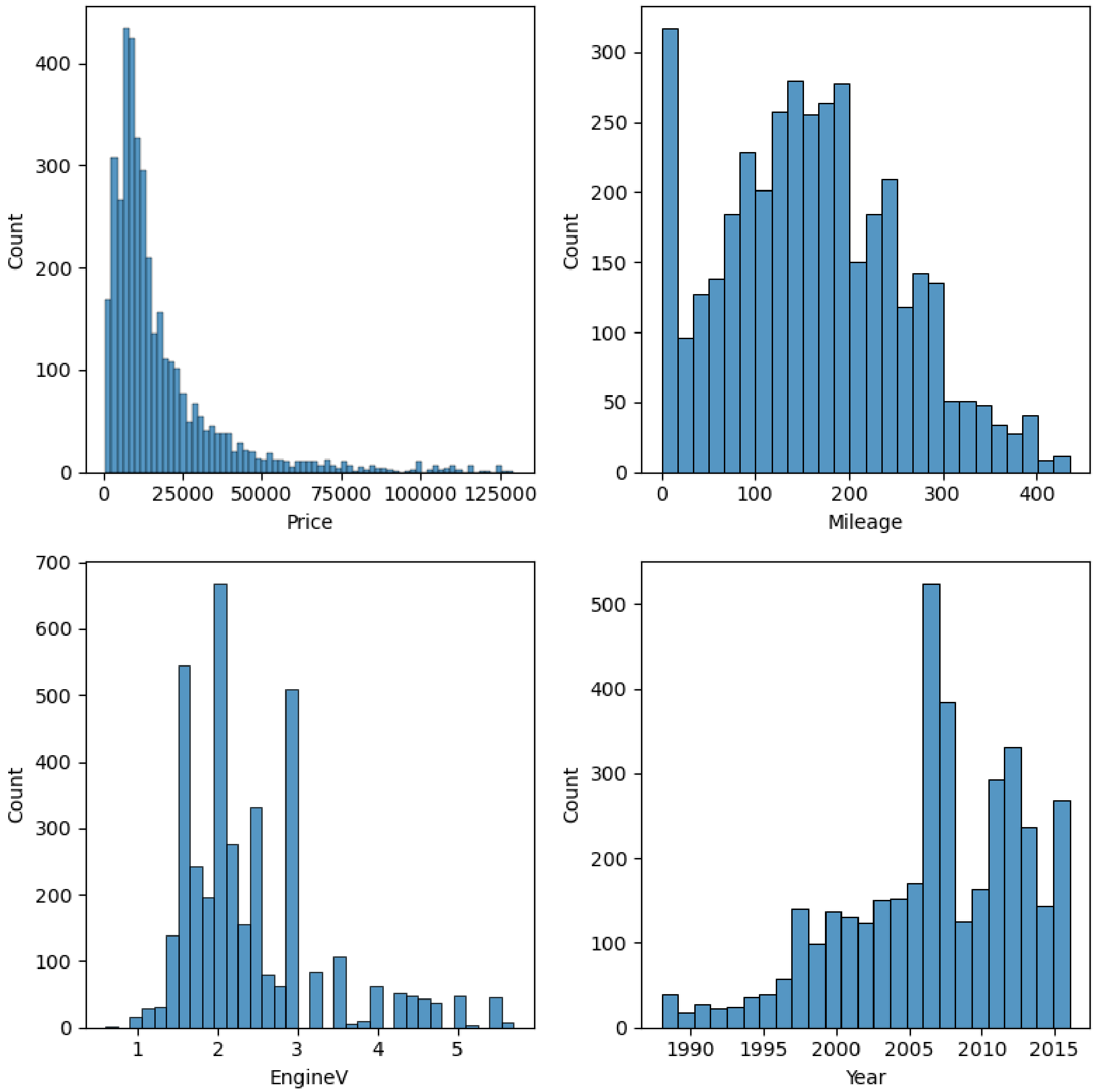
In [70]:
```
# Model has 312 unique values, which is too many for a categorical variable,
raw_data = raw_data.drop(['Model'], axis=1)
```

In [71]:
```
# check for missing values
raw_data.isnull().sum()
# if the sum is less than 5% of the total data, we can drop the rows with mi
raw_data = raw_data.dropna(axis=0)
```

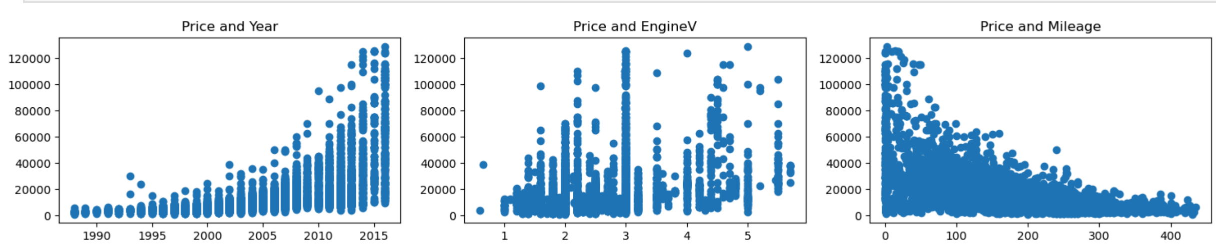
In [72]:
```
import seaborn as sns
import matplotlib.pyplot as plt
fig, axes = plt.subplots(2,2, figsize=(8,8))
sns.histplot(raw_data['Price'], ax=axes[0,0])
sns.histplot(raw_data['Mileage'], ax=axes[0,1])
sns.histplot(raw_data['EngineV'], ax=axes[1,0])
sns.histplot(raw_data['Year'], ax=axes[1,1])
plt.tight_layout()
plt.show()
# sns.displot(raw_data['year'], ax=axes[2,0])
```



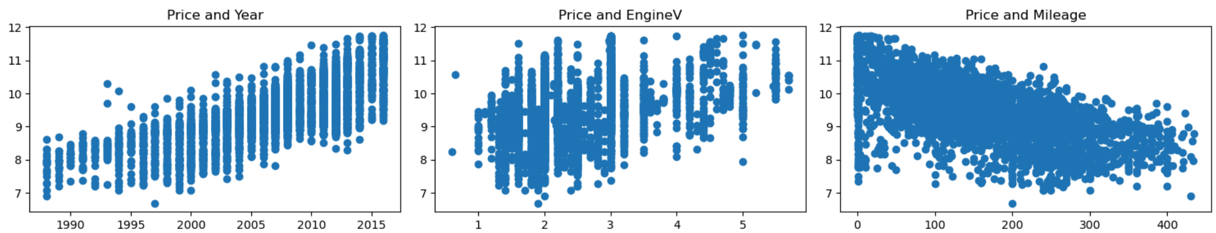
In [73]:
```
# remove outliers
q =  raw_data['Price'].quantile(0.99); raw_data = raw_data[raw_data['Price']
q =  raw_data['Mileage'].quantile(0.99); raw_data = raw_data[raw_data['Milea
q =  raw_data['EngineV'].quantile(0.99); raw_data = raw_data[raw_data['Engir
q =  raw_data['Year'].quantile(0.01); raw_data = raw_data[raw_data['Year']>c
fig, axes = plt.subplots(2,2, figsize=(8,8))
sns.histplot(raw_data['Price'], ax=axes[0,0])
sns.histplot(raw_data['Mileage'], ax=axes[0,1])
sns.histplot(raw_data['EngineV'], ax=axes[1,0])
sns.histplot(raw_data['Year'], ax=axes[1,1])
plt.tight_layout()
plt.show()
```



In [74]:
```
data = raw_data.reset_index(drop=True)
# check for linearity
fig, axes = plt.subplots(1,3, figsize=(15,3))
axes[0].scatter(data['Year'], data['Price'])
axes[0].set_title('Price and Year')
axes[1].scatter(data['EngineV'], data['Price'])
axes[1].set_title('Price and EngineV')
axes[2].scatter(data['Mileage'], data['Price'])
axes[2].set_title('Price and Mileage')
plt.tight_layout()
plt.show()
```



In [75]:
```
import numpy as np
data['Price_log'] = np.log(data['Price'])
fig, axes = plt.subplots(1,3, figsize=(15,3))
axes[0].scatter(data['Year'], data['Price_log'])
axes[0].set_title('Price and Year')
axes[1].scatter(data['EngineV'], data['Price_log'])
axes[1].set_title('Price and EngineV')
axes[2].scatter(data['Mileage'], data['Price_log'])
axes[2].set_title('Price and Mileage')
plt.tight_layout()
plt.show()
```



In [76]:
```
# check for multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
variance_inflation_factor(data[['Year', 'Mileage', 'EngineV']].values, 0)
vif = pd.DataFrame()
vif["Features"] = ['Year', 'Mileage', 'EngineV']
vif["VIF"] = [variance_inflation_factor(data[['Year', 'Mileage', 'EngineV']]
vif
```

Out[76]:

	Features	VIF
0	Year	10.823028
1	Mileage	3.798257
2	EngineV	8.262153

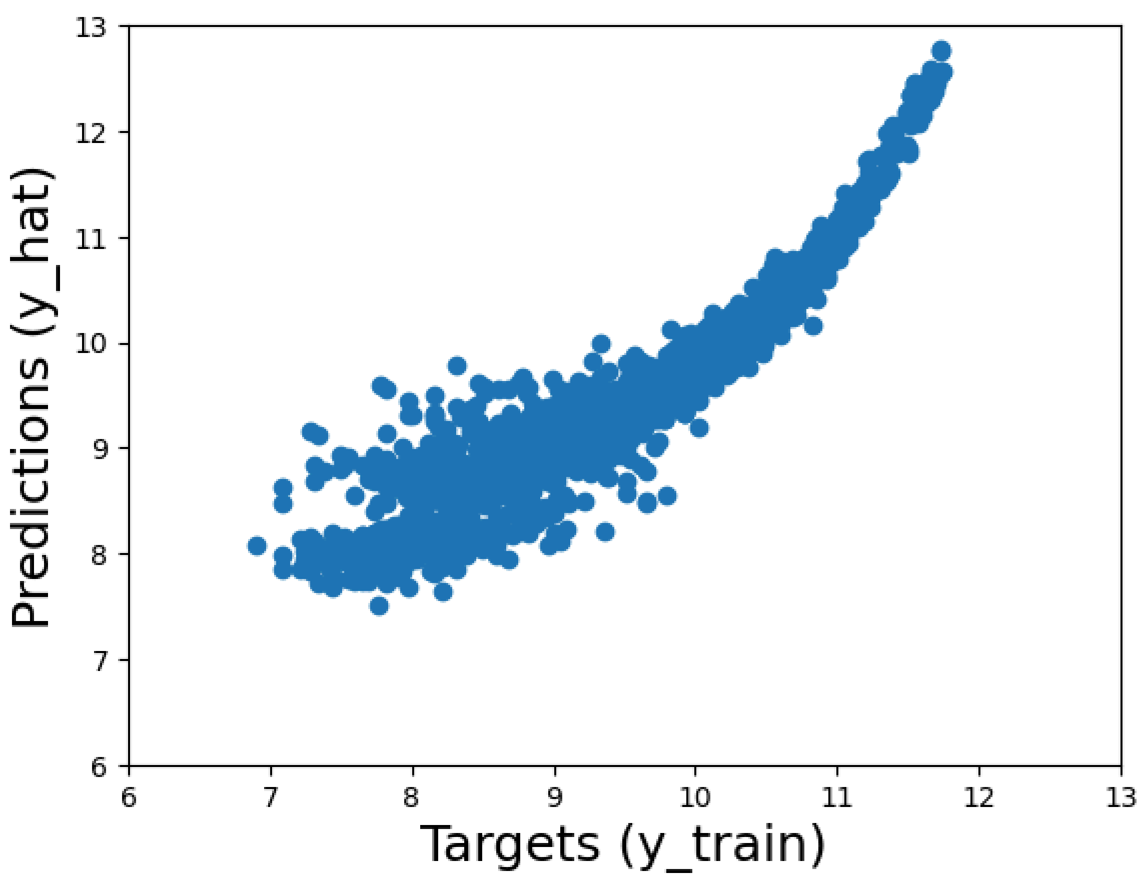
In [77]:
```
data = data.drop(['Year'], axis=1)
# create dummy variables
data_with_dummies = pd.get_dummies(data, drop_first=True)
data_with_dummies.columns.values
```

Out[77]:
```
array(['Price', 'Mileage', 'EngineV', 'Price_log', 'Brand_BMW',
       'Brand_Mercedes-Benz', 'Brand_Mitsubishi', 'Brand_Renault',
       'Brand_Toyota', 'Brand_Volkswagen', 'Body_hatch', 'Body_other',
       'Body_sedan', 'Body_vagon', 'Body_van', 'Engine Type_Gas',
       'Engine Type_Other', 'Engine Type_Petrol', 'Registration_yes'],
      dtype=object)
```

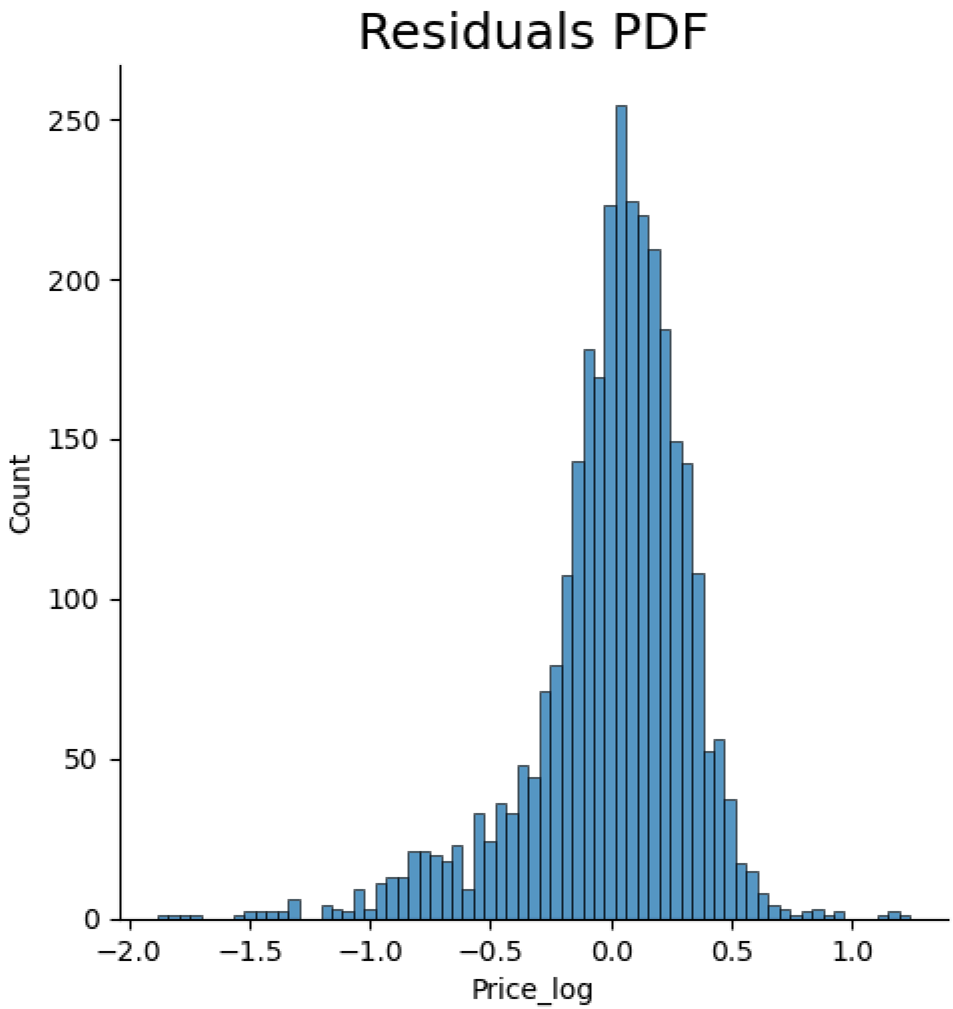
In [78]:
```
cols = ['Price_log', 'Mileage', 'EngineV', 'Brand_BMW',
        'Brand_Mercedes-Benz', 'Brand_Mitsubishi', 'Brand_Renault',
        'Brand_Toyota', 'Brand_Volkswagen', 'Body_hatch', 'Body_other',
        'Body_sedan', 'Body_vagon', 'Body_van', 'Engine Type_Gas',
        'Engine Type_Other', 'Engine Type_Petrol', 'Registration_yes']
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LinearRegression

target = data_with_dummies['Price_log']
inputs = data_with_dummies.drop(['Price_log'], axis=1)

scaler = StandardScaler()
scaler.fit(inputs)
inputs_scaled = scaler.transform(inputs)

x_train, x_test, y_train, y_test = train_test_split(inputs_scaled, target, t
model = LinearRegression()
model.fit(x_train, y_train)
print("R2 score: ", model.score(x_train, y_train))

y_hat = model.predict(x_train)
plt.scatter(y_train, y_hat)
plt.xlabel('Targets (y_train)',size=18)
plt.ylabel('Predictions (y_hat)',size=18)
plt.xlim(6,13)
plt.ylim(6,13)
plt.show()

sns.displot(y_train - y_hat)
plt.title("Residuals PDF", size=18)
```

```
R2 score:  0.8614704081308995
```

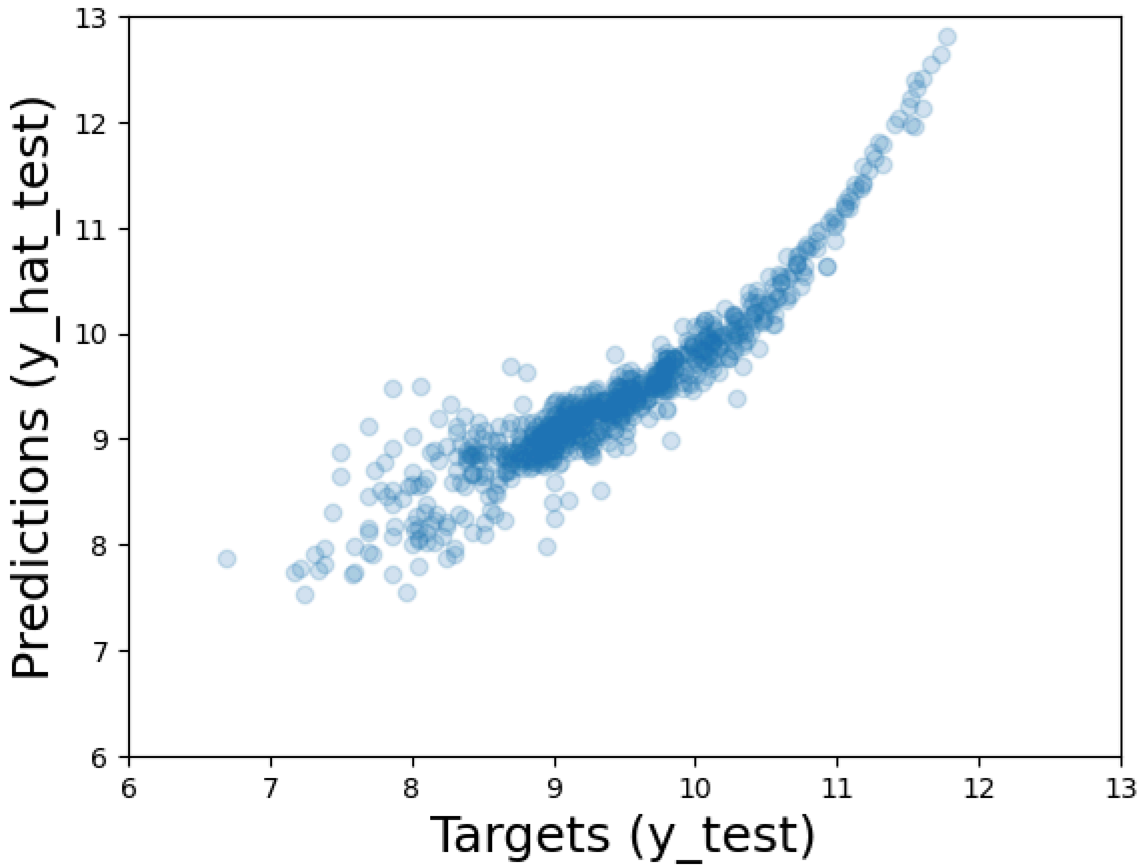


Out[78]:
```
Text(0.5, 1.0, 'Residuals PDF')
```



In [79]:

```
# Test the model
y_hat_test = model.predict(x_test)
plt.scatter(y_test, y_hat_test, alpha=0.2)
plt.xlabel('Targets (y_test)',size=18)
plt.ylabel('Predictions (y_hat_test)',size=18)
plt.xlim(6,13)
plt.ylim(6,13)
plt.show()
```



In [80]:
```
df_pf = pd.DataFrame(np.exp(y_hat_test), columns=['Prediction'])
y_test = y_test.reset_index(drop=True)
df_pf['Target'] = np.exp(y_test)
df_pf['Residual'] = df_pf['Target'] - df_pf['Prediction']
df_pf['Difference%'] = np.absolute(df_pf['Residual']/df_pf['Target']*100)
df_pf.describe()
```

Out[80]:

	Prediction	Target	Residual	Difference%
count	768.000000	768.000000	768.000000	768.000000
mean	18692.026402	17340.211081	-1351.815321	25.617407
std	32226.642076	18301.452188	17529.590830	37.090122
min	1858.702977	800.000000	-238592.740056	0.026298
25%	7613.383602	7337.500000	-1069.363883	7.611709
50%	10641.799282	10999.000000	453.542690	16.043282
75%	16598.427713	20000.000000	2688.084032	27.069728
max	367814.740056	129222.000000	17548.773246	405.800953