Using wrap method to refine feature selection

Read clean data

In [1]:
```
import pandas as pd

# Specify the path to your CSV file
file_path = 'Group_2_clean_Data..csv'

# Load the CSV file into a DataFrame
df = pd.read_csv(file_path)

df.head()
```

Out[1]:

	communityname	State	countyCode	communityCode	fold	pop	perHoush	pctBlack	pctWhite	pctAsian	...	burglaries
0	149.0	28.0	55.0	509.0	1.0	11980.0	3.10	1.37	91.78	6.50	...	14.1
1	1034.0	35.0	58.0	424.0	1.0	23123.0	2.82	0.80	95.57	3.44	...	57.0
2	1780.0	34.0	114.0	959.0	1.0	29344.0	2.43	0.74	94.33	3.43	...	274.0
3	664.0	31.0	53.0	213.0	1.0	16656.0	2.40	1.70	97.35	0.50	...	225.0
4	140.0	22.0	82.0	471.0	1.0	11245.0	2.76	0.53	89.16	1.17	...	91.0

5 rows × 125 columns

In [2]:
```
# Assuming `df` is your DataFrame:
df_feature = df.iloc[:, 5:-18]  # Select all rows and columns from index 5 to the 18th-to-last
df_target = df['burglaries']  # Select the 'violentPerPop' column as the target variable


df_feature.head(5)
```

Out[2]:

	pop	perHoush	pctBlack	pctWhite	pctAsian	pctHisp	pct12-21	pct12-29	pct16-24	pct65up	...	persHomeless	pctForeignBo
0	11980.0	3.10	1.37	91.78	6.50	1.88	12.47	21.44	10.93	11.33	...	0.1	10
1	23123.0	2.82	0.80	95.57	3.44	0.85	11.01	21.30	10.48	17.18	...	0.0	8
2	29344.0	2.43	0.74	94.33	3.43	2.35	11.36	25.88	11.01	10.28	...	0.0	5
3	16656.0	2.40	1.70	97.35	0.50	0.70	12.55	25.20	12.19	17.57	...	0.0	2
4	11245.0	2.76	0.53	89.16	1.17	0.52	24.46	40.53	28.69	12.65	...	0.0	1

5 rows × 102 columns

In [6]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import pandas as pd

n_top_features = 30

X_train, X_test, y_train, y_test = train_test_split(
    df_feature, df_target, test_size=0.2, random_state=42
)

rf_model = RandomForestRegressor(random_state=42, n_estimators=100)
rf_model.fit(X_train, y_train)

feature_importances = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

top_features = feature_importances.head(n_top_features)['Feature'].tolist()
print(f"Top {n_top_features} Features: {top_features}")

X_train_top = X_train[top_features]
X_test_top = X_test[top_features]
```

```
rf_model_top = RandomForestRegressor(random_state=42, n_estimators=50)
rf_model_top.fit(X_train_top, y_train)

y_pred_top = rf_model_top.predict(X_test_top)
test_mse_top = mean_squared_error(y_test, y_pred_top)
test_r2_top = r2_score(y_test, y_pred_top)

y_train_pred_top = rf_model_top.predict(X_train_top)
train_mse_top = mean_squared_error(y_train, y_train_pred_top)
train_r2_top = r2_score(y_train, y_train_pred_top)

print(f"Training Set Metrics with Top {n_top_features} Features:")
print(f"  - Mean Squared Error: {train_mse_top:.2f}")
print(f"  - R-squared: {train_r2_top:.2f}")

print(f"Testing Set Metrics with Top {n_top_features} Features:")
print(f"  - Mean Squared Error: {test_mse_top:.2f}")
print(f"  - R-squared: {test_r2_top:.2f}")
```

```
Top 30 Features: ['persPoverty', 'persUrban', 'numForeignBorn', 'kidsBornNevrMarr', 'pop', 'houseVacant', 'persEmergS
helt', 'pctUsePubTrans', 'persHomeless', 'pctLargHous', 'pctPersOwnOccup', 'landArea', 'pctImmig-5', 'pctFemDivorc',
'pctWorkMom-6', 'pctSmallHousUnits', 'pctSameCounty-5', 'pctHousOwnerOccup', 'pctMaleNevMar', 'NAperCap', 'pctSameHou
se-5', 'persPerOccupHous', 'pctFgnImmig-3', 'pctMaleDivorc', 'pctOccupMgmt', 'medRentpctHousInc', 'whitePerCap', 'pct
EmployMfg', 'pctLowEdu', 'pct16-24']
Training Set Metrics with Top 30 Features:
  - Mean Squared Error: 530342.80
  - R-squared: 0.95
Testing Set Metrics with Top 30 Features:
  - Mean Squared Error: 190513.61
  - R-squared: 0.93
```

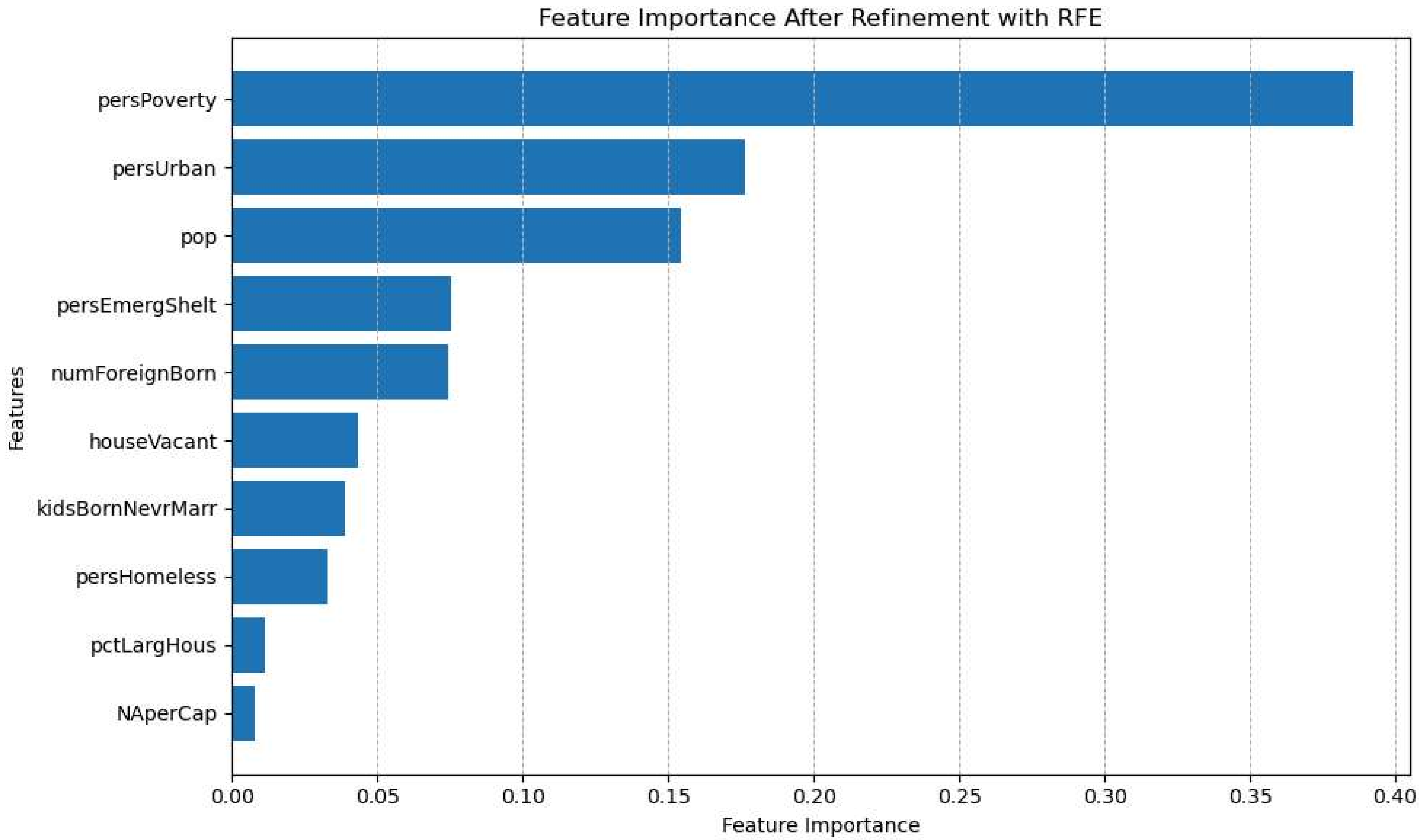
Experimenting with RFE

In [4]:

```
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Initialize Random Forest Regressor
```

```python
rf = RandomForestRegressor(random_state=42, n_estimators=50)

# Recursive Feature Elimination (RFE) for feature refinement
rfe = RFE(estimator=rf, n_features_to_select=10)  # Set the desired number of features
rfe.fit(X_train[top_features], y_train)

# Get the refined features
refined_features = X_train[top_features].columns[rfe.support_]
print(f"Refined Features: {list(refined_features)}")

# Train and evaluate the final model with refined features
X_train_refined = X_train[refined_features]
X_test_refined = X_test[refined_features]
rf.fit(X_train_refined, y_train)

# Predictions and metrics
y_pred = rf.predict(X_test_refined)
test_mse = mean_squared_error(y_test, y_pred)
test_r2 = r2_score(y_test, y_pred)

print(f"Final Model Performance with Refined Features:")
print(f"  - Mean Squared Error: {test_mse:.2f}")
print(f"  - R-squared: {test_r2:.2f}")

# Rank features by importance
sorted_indices = rf.feature_importances_.argsort()[::-1]
sorted_features = [refined_features[i] for i in sorted_indices]
sorted_importances = rf.feature_importances_[sorted_indices]

# Plot feature importances for refined features
plt.figure(figsize=(10, 6))
plt.barh(sorted_features, sorted_importances)
plt.xlabel("Feature Importance")
plt.ylabel("Features")
plt.title("Feature Importance After Refinement with RFE")
plt.gca().invert_yaxis()  # Invert y-axis to display the most important feature at the top
plt.grid(axis="x", linestyle="--", linewidth=0.7)
plt.tight_layout()
plt.savefig("feature_importance_rfe.png", format="png", dpi=300)
plt.show()
```

```
Refined Features: ['persPoverty', 'persUrban', 'numForeignBorn', 'kidsBornNevrMarr', 'pop', 'houseVacant', 'persEmerg
Shelt', 'persHomeless', 'pctLargHous', 'NAperCap']
Final Model Performance with Refined Features:
  - Mean Squared Error: 247211.18
  - R-squared: 0.91
```



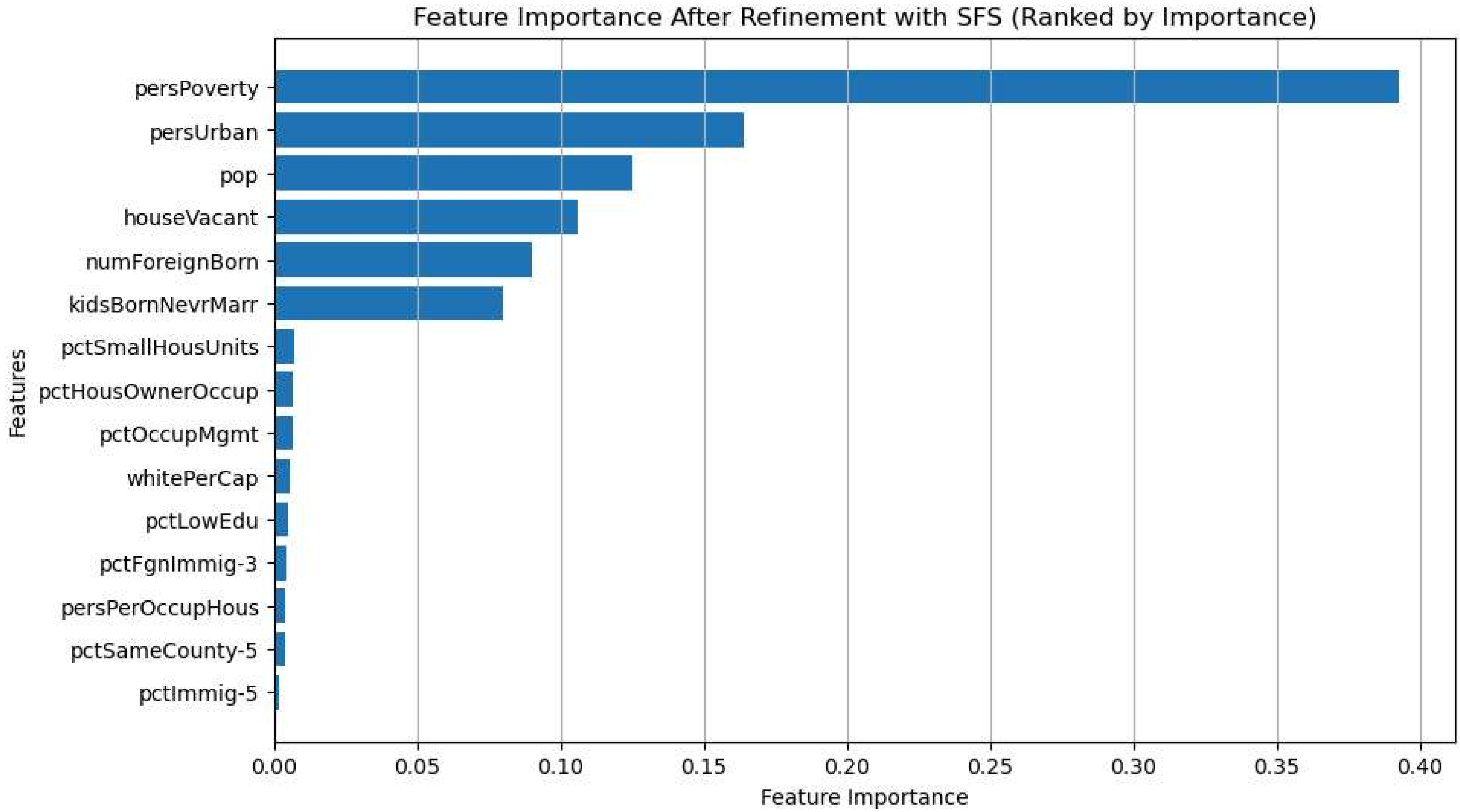
experimenting model with SFS method

In [5]:
```python
import matplotlib.pyplot as plt
from sklearn.feature_selection import SequentialFeatureSelector
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Initialize Random Forest Regressor
rf = RandomForestRegressor(random_state=42, n_estimators=50)

# Sequential Feature Selector for forward selection refinement
sfs = SequentialFeatureSelector(
    estimator=rf,
    n_features_to_select="auto",  # Automatically determine the optimal subset
    direction="forward",  # Forward selection
    scoring="r2",  # Use R-squared for performance evaluation
    cv=5,  # 5-fold cross-validation
    n_jobs=-1
)

# Fit SFS on the top 30 features
sfs.fit(X_train[top_features], y_train)

# Get the refined features
refined_features = X_train[top_features].columns[sfs.get_support()]
print(f"Refined Features: {list(refined_features)}")

# Train and evaluate the final model with refined features
X_train_refined = X_train[refined_features]
X_test_refined = X_test[refined_features]
rf.fit(X_train_refined, y_train)

# Predictions and metrics
y_pred = rf.predict(X_test_refined)
test_mse = mean_squared_error(y_test, y_pred)
test_r2 = r2_score(y_test, y_pred)

print(f"Final Model Performance with Refined Features:")
print(f"  - Mean Squared Error: {test_mse:.2f}")
print(f"  - R-squared: {test_r2:.2f}")
# Plot feature importances for refined features sorted by importance
sorted_indices = rf.feature_importances_.argsort()[::-1]  # Sort indices in descending order of importance
sorted_features = [refined_features[i] for i in sorted_indices]  # Sort feature names
sorted_importances = rf.feature_importances_[sorted_indices]  # Sort importances

plt.figure(figsize=(10, 6))
```

```
plt.barh(sorted_features, sorted_importances)
plt.xlabel("Feature Importance")
plt.ylabel("Features")
plt.title("Feature Importance After Refinement with SFS (Ranked by Importance)")
plt.gca().invert_yaxis()  # Invert y-axis to display the most important feature at the top
plt.grid(axis="x")
plt.savefig("feature_importance_SFS.png", format="png", dpi=300)
plt.show()
```

```
Refined Features: ['persPoverty', 'persUrban', 'numForeignBorn', 'kidsBornNevrMarr', 'pop', 'houseVacant', 'pctImmig-5', 'pctSmallHousUnits', 'pctSameCounty-5', 'pctHousOwnerOccup', 'persPerOccupHous', 'pctFgnImmig-3', 'pctOccupMgmt', 'whitePerCap', 'pctLowEdu']
Final Model Performance with Refined Features:
  - Mean Squared Error: 273425.36
  - R-squared: 0.90
```


Feature Importance After Refinement with SFS (Ranked by Importance)
persPoverty
persUrban
pop
houseVacant
numForeignBorn
kidsBornNevrMarr
pctSmallHousUnits
pctHousOwnerOccup
pctOccupMgmt
whitePerCap
pctLowEdu
pctFgnImmig-3
persPerOccupHous
pctSameCounty-5
pctImmig-5
Features
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
Feature Importance

```
In [ ]:
```