Modeling With and Without Outliers

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        sns.set_context('poster')
        import random
```

```
In [2]: from project_helper import *
```

Import, Split and Standardize Data

```
In [3]: df = pd.DataFrame.from_csv('../data/merged/all_data_2006_to_2016.csv', index_col=None)
```

In [4]:

```
# split train/test by indices before removing outliers
# so that we can have a consistent split between tests

# seed for consistent splits
random.seed(1636)

# all idxs
idxs = list(range(len(df)))

# idxs of outliers
outlier_idxs = list((df.MSA_abbr == 'NEW_ORLEANS_LA').nonzero()[0])
outlier_idxs += list(((df.MSA_abbr == 'MEMPHIS_TN') & (df.year == 2016)).nonzero()[0])
outlier_idxs += list(((df.MSA_abbr == 'BATON_ROUGE_LA') & (df.year == 2007)).nonzero()[0])

# shuffle and split
random.shuffle(idxs)
split = int(len(idxs)*0.7)
train_all = idxs[:split]
test_all = idxs[split:]

# remove outliers
train_no = [idx for idx in train_all if idx not in outlier_idxs]
test_no = [idx for idx in test_all if idx not in outlier_idxs]
```

In [5]:

```
# drop MSA names
df = df.drop(['MSA_corr','MSA_orig','MSA_abbr'], axis=1)
```

In [6]:

```python
# separate labels and features

label_col = 'murder_per_100_k'

# with outliers
x_train_all = df.iloc[train_all].drop([label_col], axis=1)
y_train_all = df.iloc[train_all][label_col]
x_test_all = df.iloc[test_all].drop([label_col], axis=1)
y_test_all = df.iloc[test_all][label_col]

# without outliers
x_train_no = df.iloc[train_no].drop([label_col], axis=1)
y_train_no = df.iloc[train_no][label_col]
x_test_no = df.iloc[test_no].drop([label_col], axis=1)
y_test_no = df.iloc[test_no][label_col]

print('All Sizes match: {}'.format(len(x_train_all)==len(y_train_all)))
print('Clean Sizes match: {}'.format(len(x_train_no)==len(y_train_no)))
```

```
All Sizes match: True
Clean Sizes match: True
```

In [7]:

```python
# standardize data

from sklearn.preprocessing import StandardScaler

# with outliers
standardizer = StandardScaler().fit(x_train_all)
x_train_all = standardizer.transform(x_train_all)
x_test_all = standardizer.transform(x_test_all)

# no outliers
standardizer = StandardScaler().fit(x_train_no)
x_train_no = standardizer.transform(x_train_no)
x_test_no = standardizer.transform(x_test_no)
```

In [8]:

```
from sklearn.linear_model import LinearRegression, RidgeCV, LassoCV, BayesianRidge, HuberRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.svm import SVR
```

In [9]:

```
# instantiate and fit models
def make_models(x_train, y_train):
    md = dict()

    md['linear'] = LinearRegression().fit(x_train, y_train)
    md['ridge'] = RidgeCV(cv=5).fit(x_train, y_train)
    md['huber'] = GridSearchCV(HuberRegressor(),{'epsilon': [1.0,1.2,1.4,1.6,1.8]}).fit(x_train, y_t
    md['knn'] = GridSearchCV(KNeighborsRegressor(),{'n_neighbors':[5,10,20,40]}).fit(x_train, y_trai
    md['adaboost'] = GridSearchCV(AdaBoostRegressor(), {'learning_rate':[0.1,0.3,0.6,1.0]}).fit(x_tr
    md['svr'] = GridSearchCV(SVR(), {'C':[0.01,0.1,1,10,100],'epsilon':[0.001,0.01,0.1,1,10]}).fit(x

    return md
```

Fit Models

In [10]:

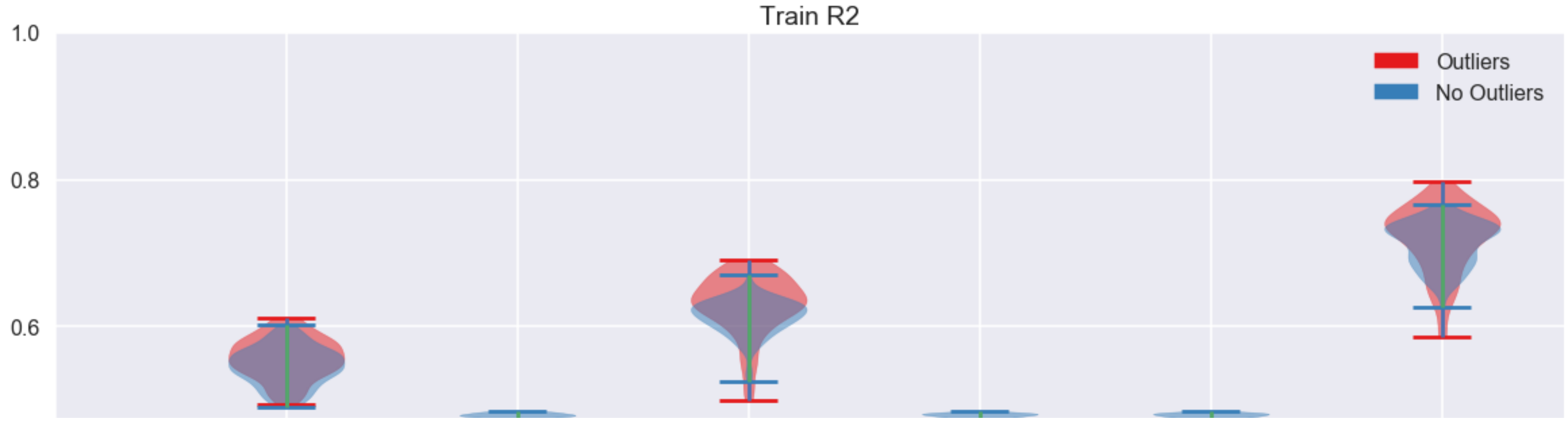
```
# with outliers
exp_1 = run_experiment(make_models, 100, x_train_all, y_train_all, x_test_all, y_test_all)

# without outliers
exp_2 = run_experiment(make_models, 100, x_train_no, y_train_no, x_test_no, y_test_no)
```

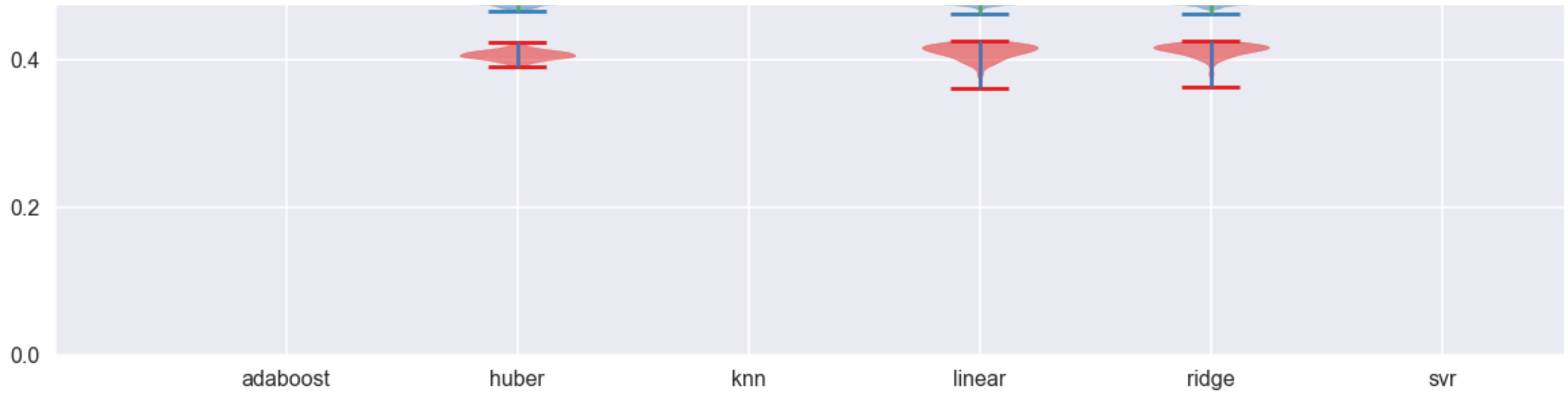
```
/Users/davidloving/anaconda3/envs/tf-gpu/lib/python3.6/site-packages/scipy/linalg/basic.py:1226:
RuntimeWarning: internal gelsd driver lwork query error, required iwork dimension not returned. T
his is likely the result of LAPACK bug 0038, fixed in LAPACK 3.2.2 (released July 21, 2010). Fall
ing back to 'gelss' driver.
  warnings.warn(mesg, RuntimeWarning)
```

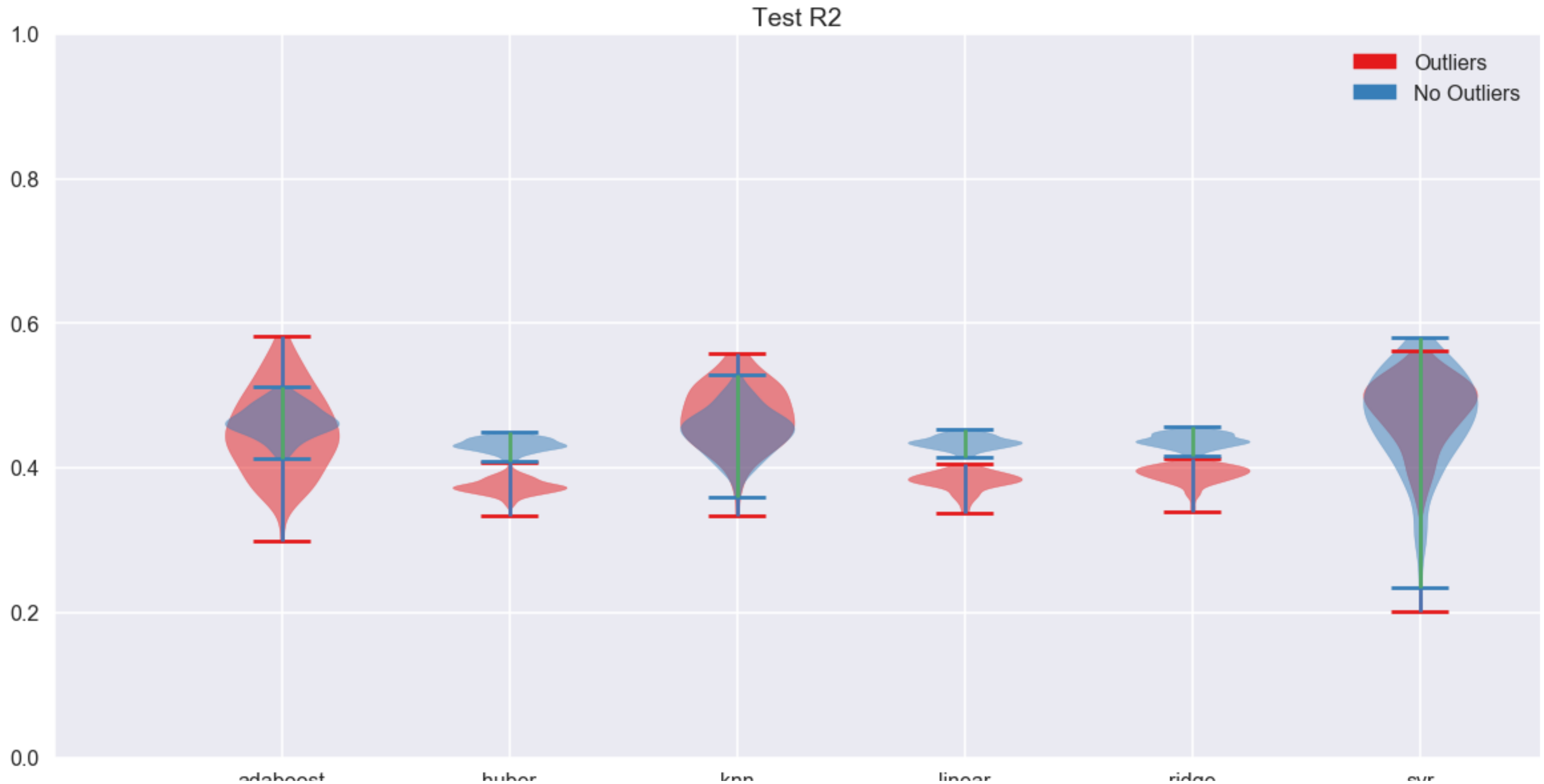
Accuracy Results

In [11]:

```
colors = plt.cm.Set1.colors

violin_plots([exp_1, exp_2],
             ['Train R2','Test R2'],
             experiment_name=['Outliers','No Outliers'],
             center_zero=False,
             cmap=colors)
```




0.4
0.2
0.0
adaboost
huber
knn
linear
ridge
svr


Test R2
1.0
0.8
0.6
0.4
0.2
0.0
🟥 Outliers
🟦 No Outliers
adaboost
huber
knn
linear
ridge
svr

Outlier Effects on Confidence Intervals

In [12]:

```
# instantiate and fit models
def make_linear_models(x_train, y_train):
    md = dict()

    md['linear'] = LinearRegression().fit(x_train, y_train)
    md['ridge'] = RidgeCV(cv=15).fit(x_train, y_train)
    md['lasso'] = LassoCV(cv=15).fit(x_train, y_train)
    md['huber'] = GridSearchCV(HuberRegressor(),{'epsilon': [1.0,1.2,1.4,1.6,1.8]}).fit(x_train, y_t

    return md
```

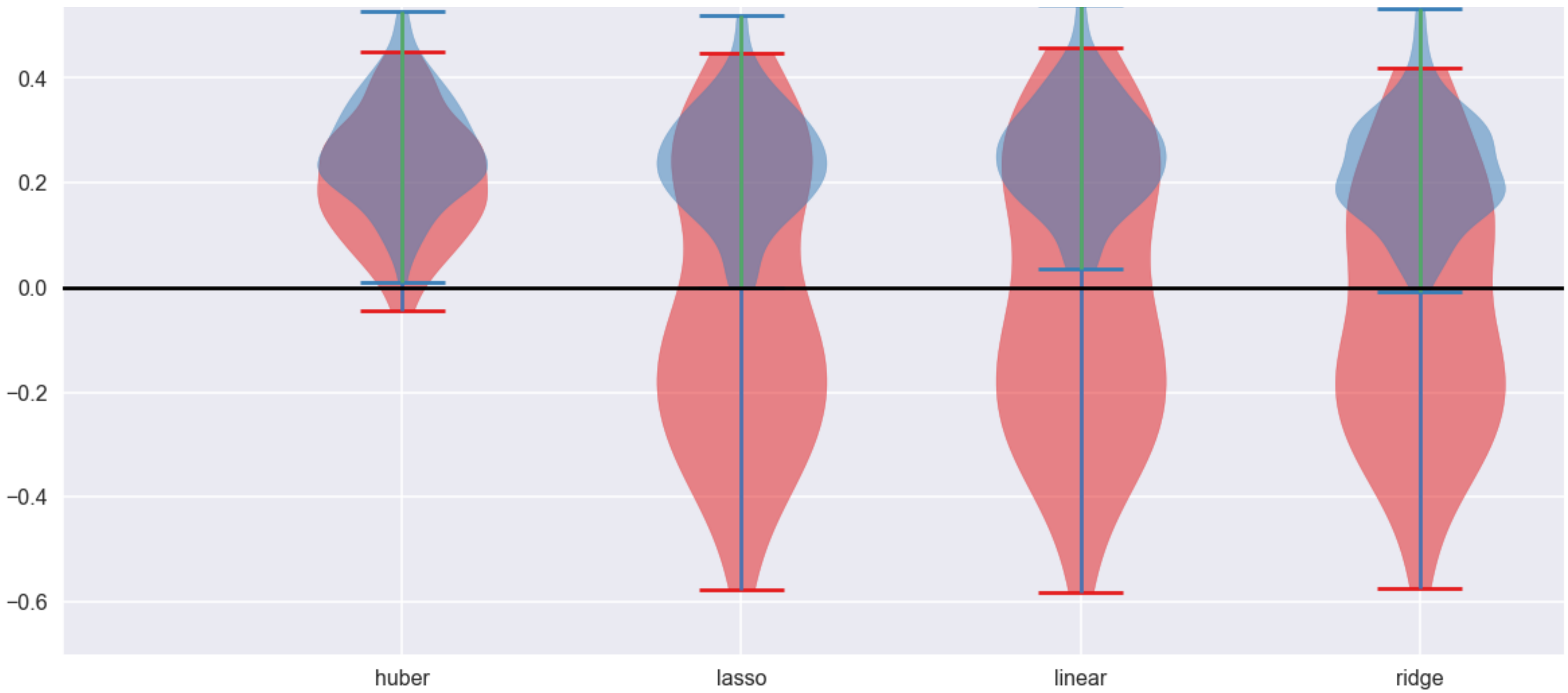
In [13]:

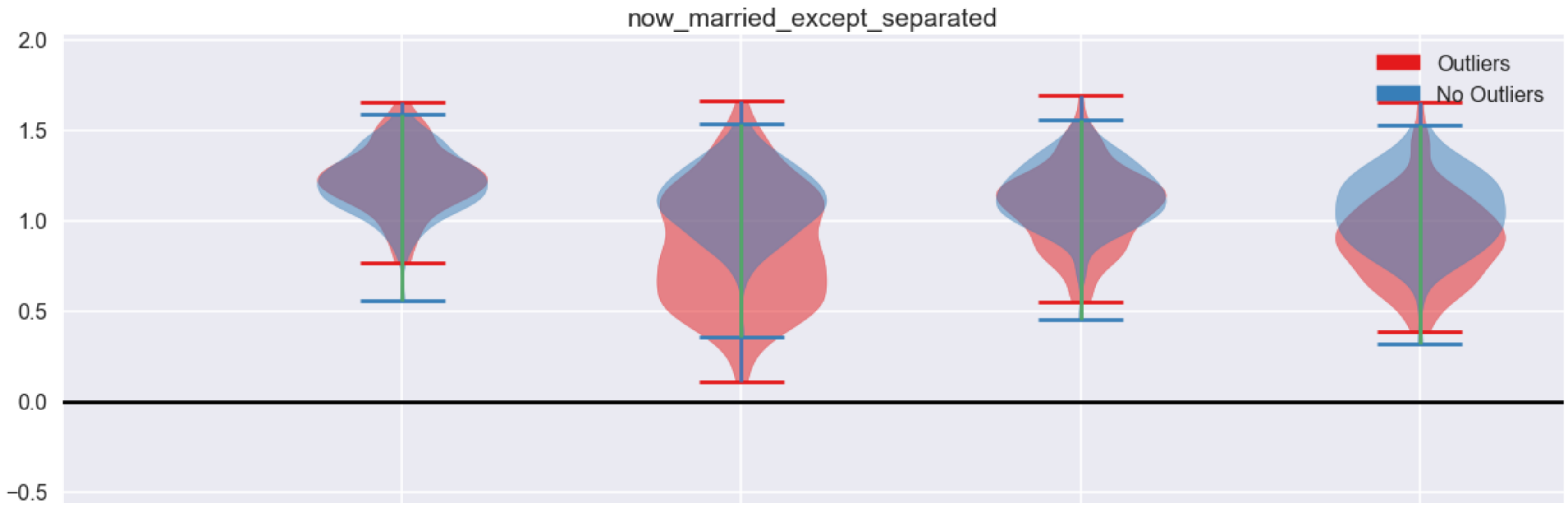
```
coeff_names = df.drop('murder_per_100_k',axis=1).columns

# with outliers
exp_3 = run_experiment(make_linear_models, 100, x_train_all, y_train_all, x_test_all, y_test_all, co

# without outliers
exp_4 = run_experiment(make_linear_models, 100, x_train_no, y_train_no, x_test_no, y_test_no, coeff_
```

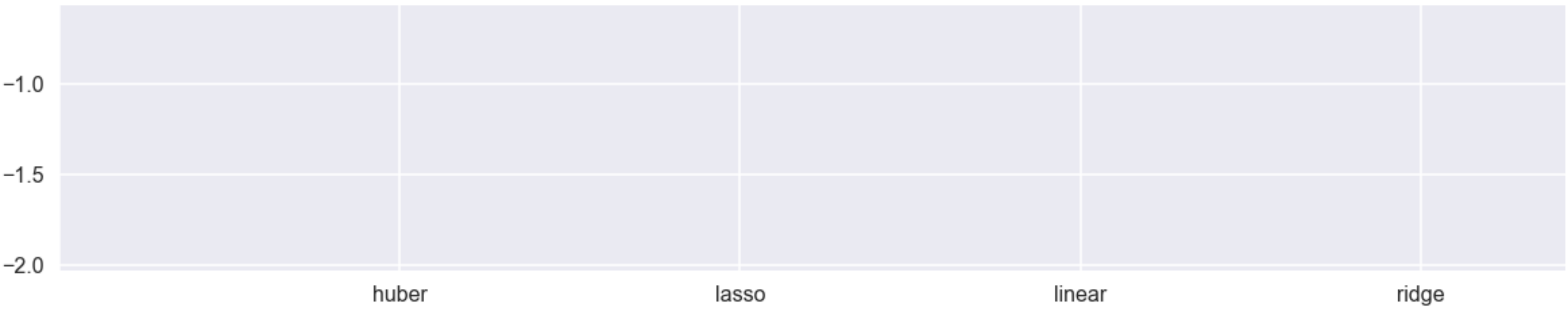
Confidence Results

In [15]:

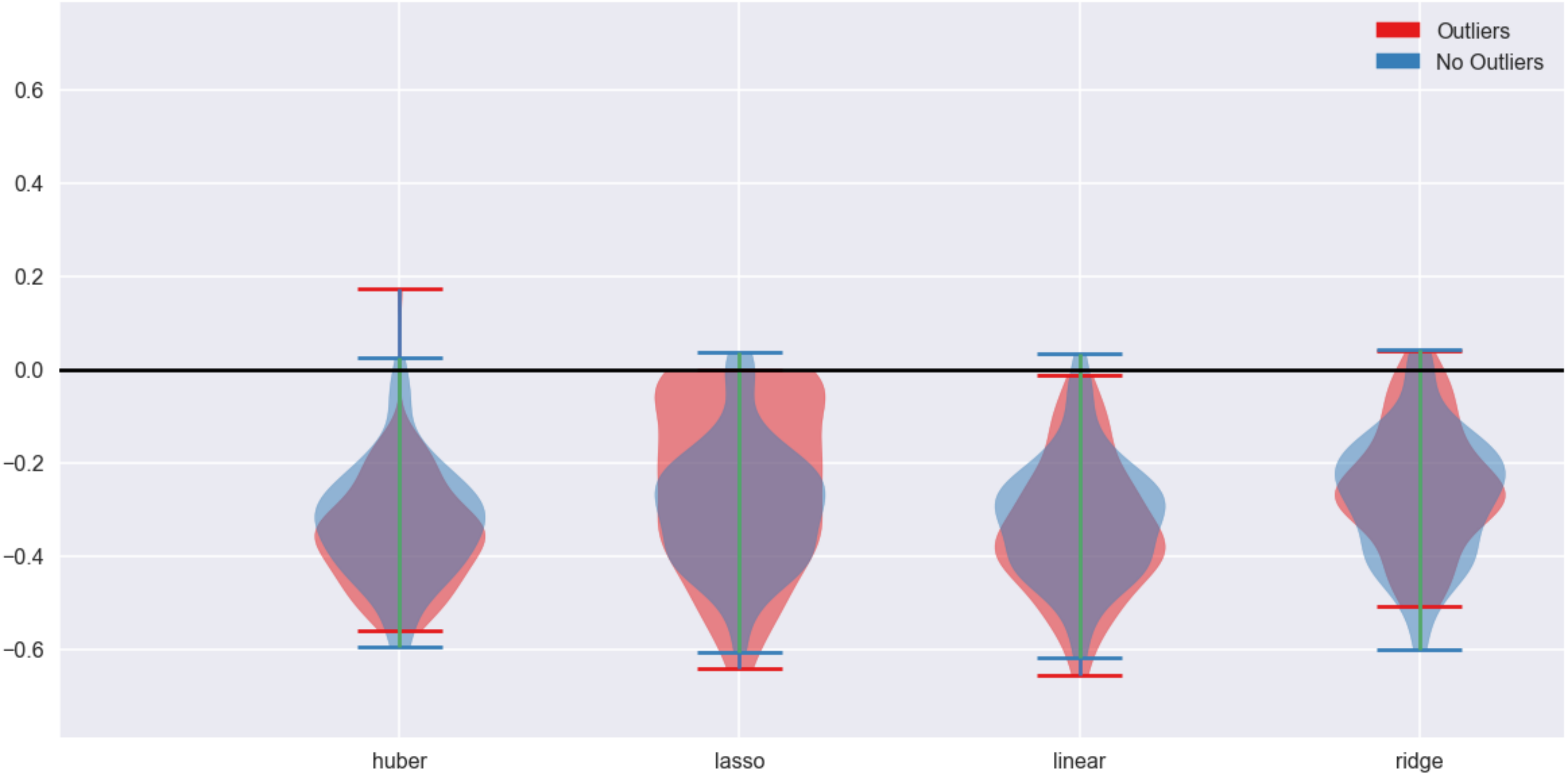
```
violin_plots([exp_3, exp_4], coeff_names, experiment_name=['Outliers','No Outliers'], cmap=colors)
```


0.4
0.2
0.0
−0.2
−0.4
−0.6
huber
lasso
linear
ridge

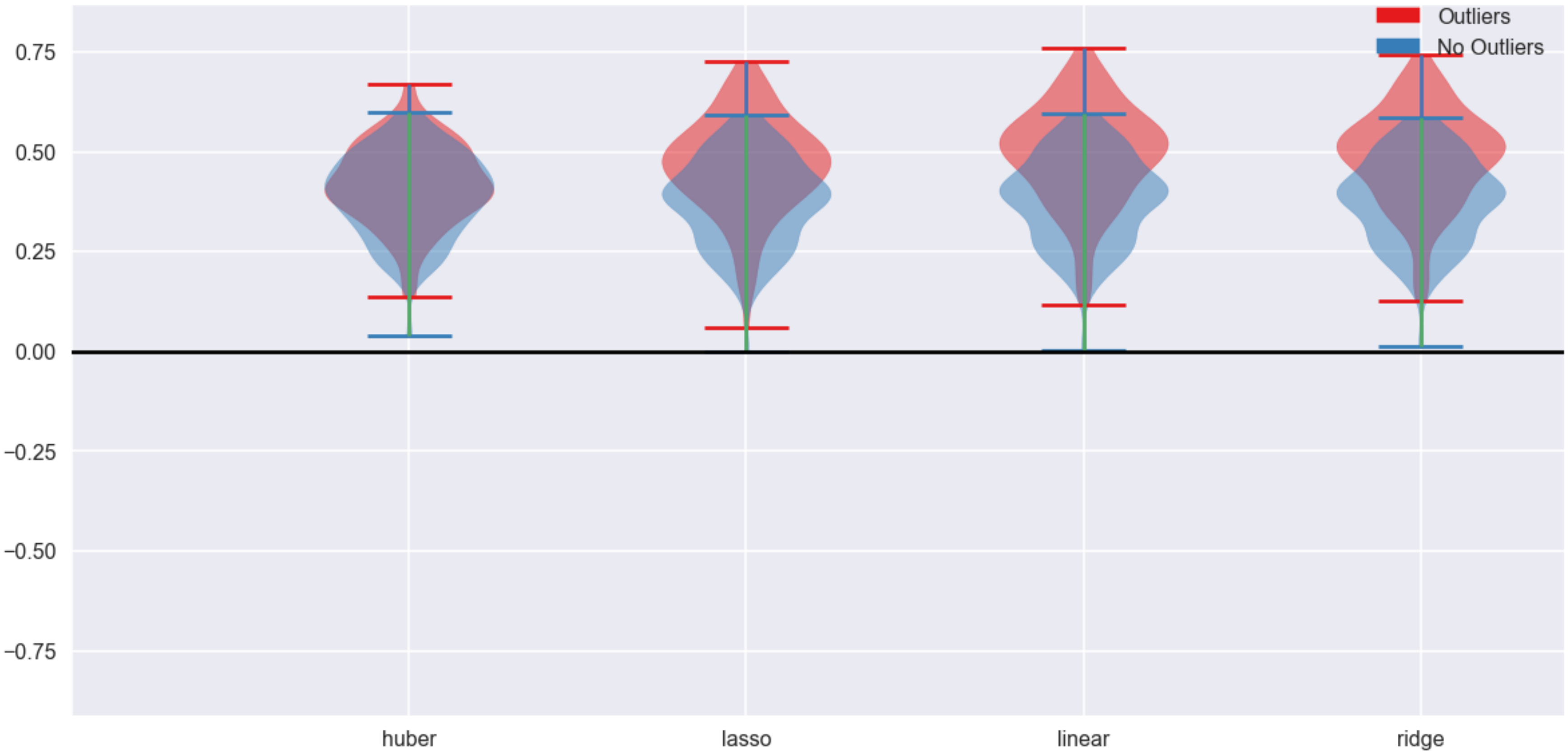

now_married_except_separated
2.0
1.5
1.0
0.5
0.0
−0.5
🟥 Outliers
🟦 No Outliers

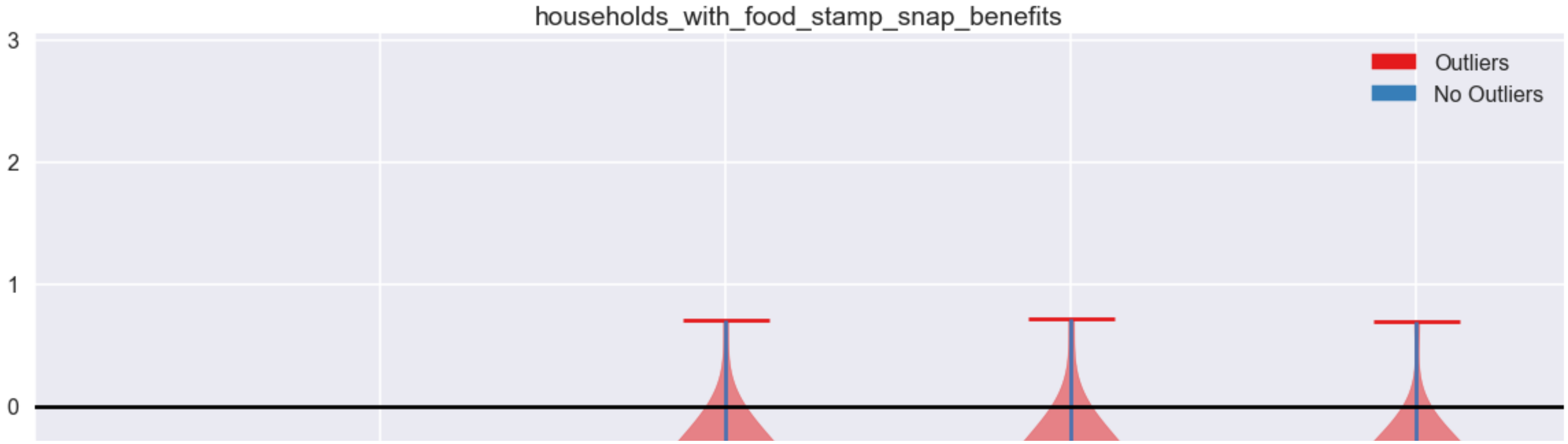


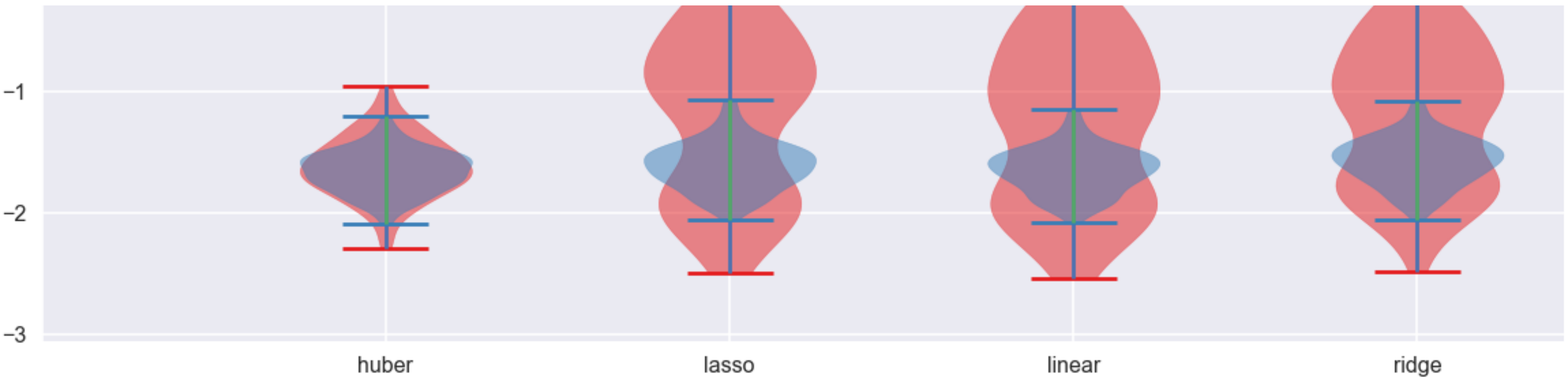
less_than_high_school_diploma



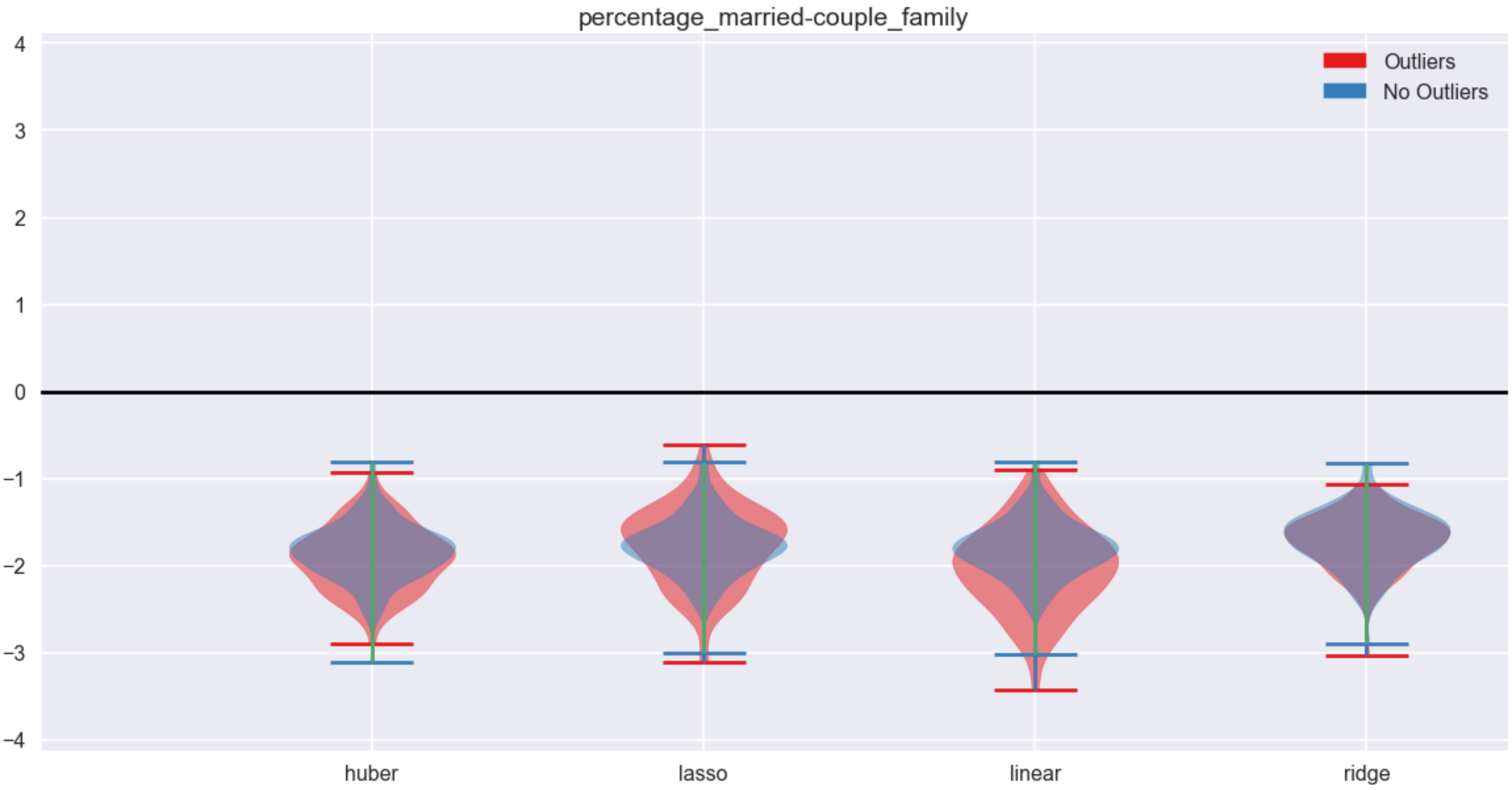
unmarried_portion_of_women_15_to_50_years_who_had_a_birth_in_past_12_months


Outliers
No Outliers
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
huber
lasso
linear
ridge

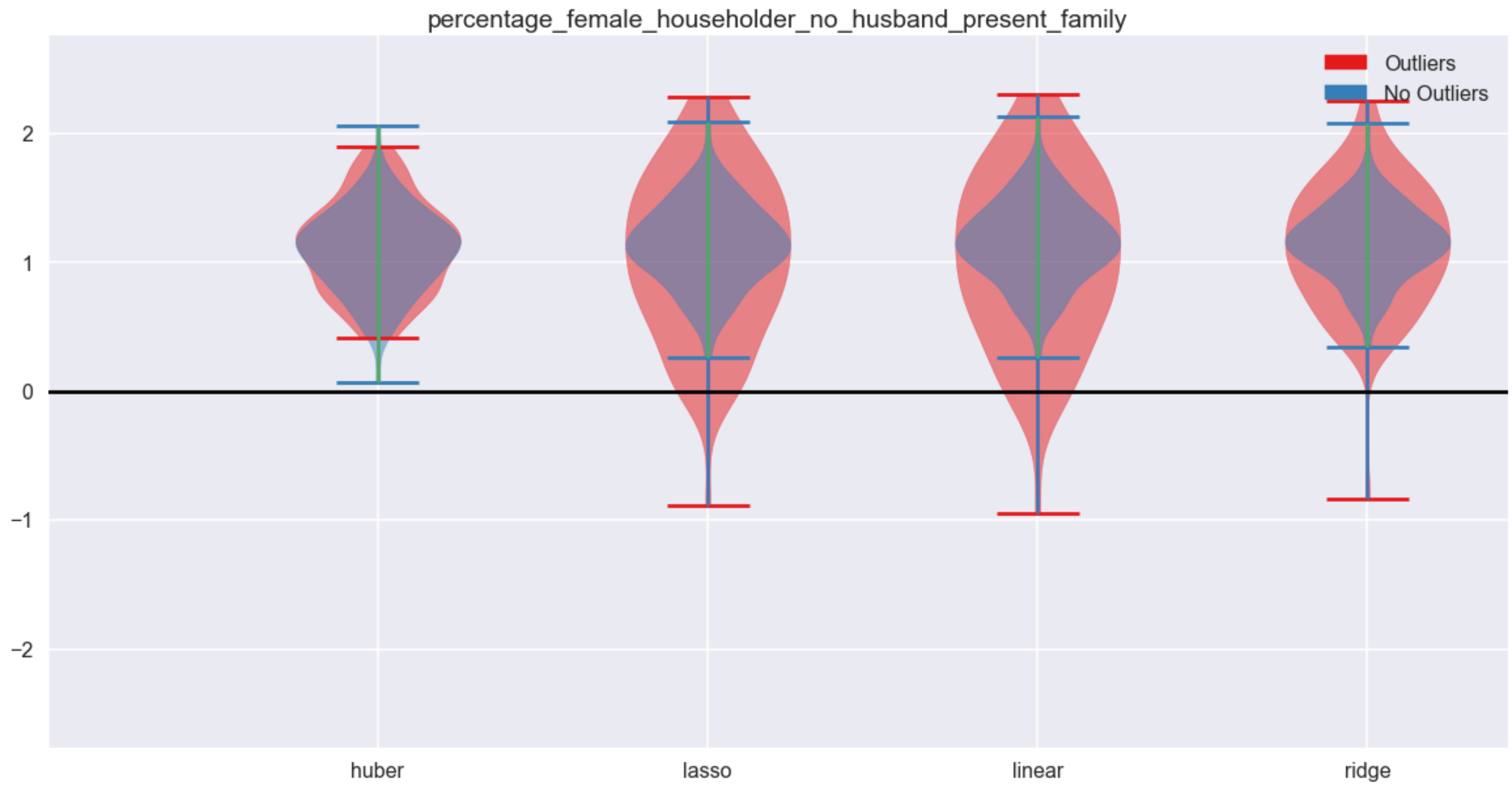

households_with_food_stamp_snap_benefits
Outliers
No Outliers
3
2
1
0

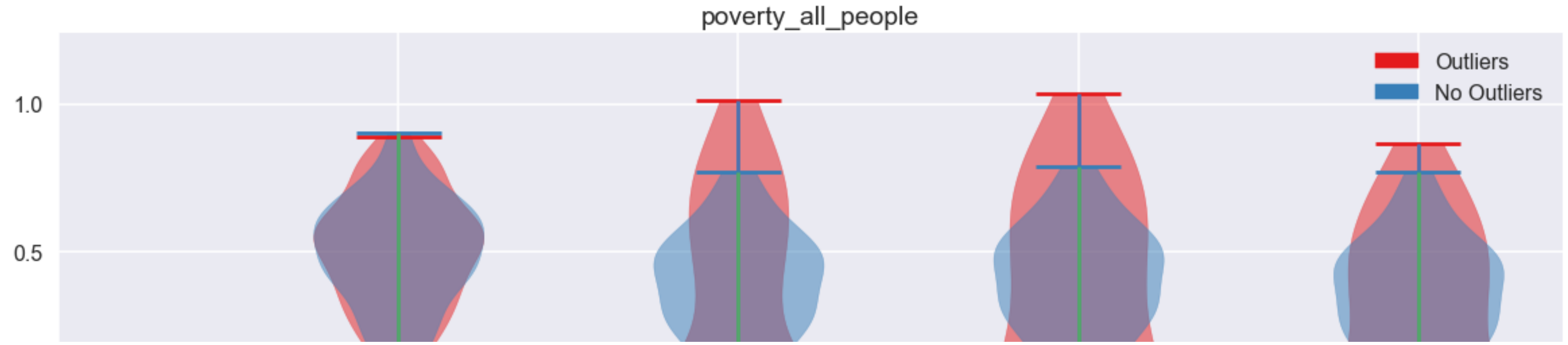


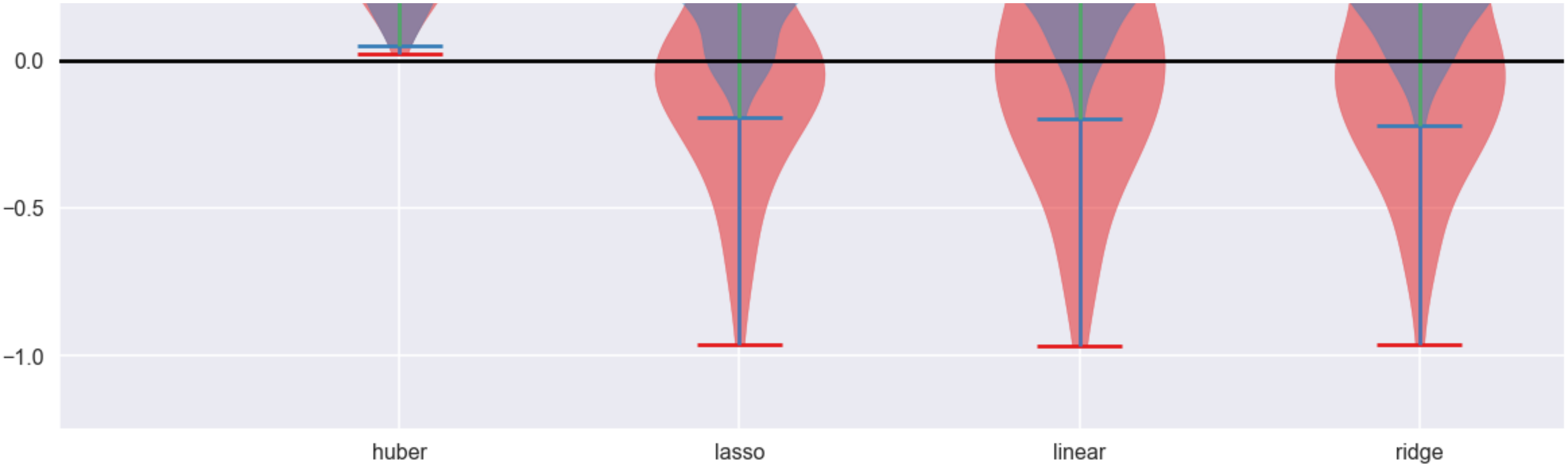
−1
−2
−3
huber
lasso
linear
ridge

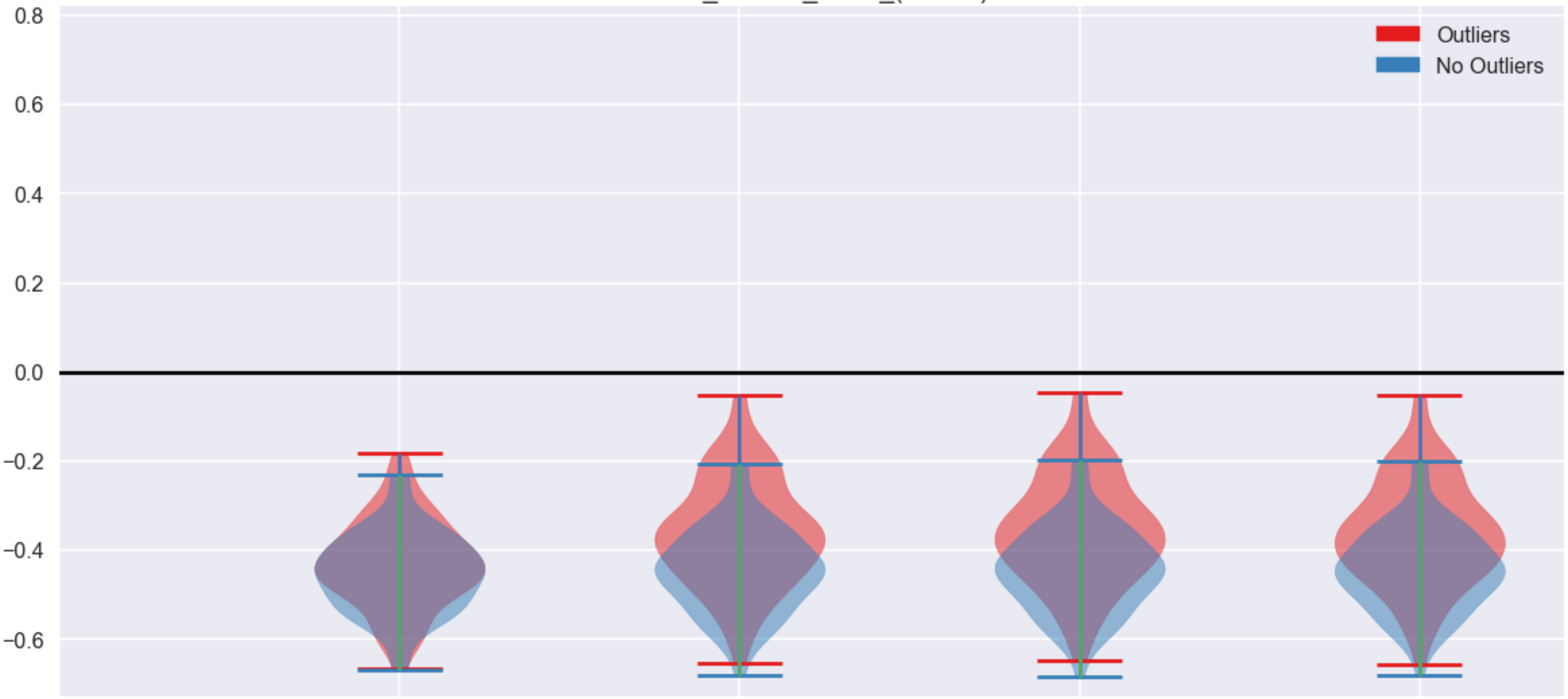


percentage_married-couple_family
🟥 Outliers
🟦 No Outliers
4
3
2
1
0
−1
−2
−3
−4
huber
lasso
linear
ridge


percentage_female_householder_no_husband_present_family
Outliers
No Outliers
2
1
0
−1
−2
huber
lasso
linear
ridge


poverty_all_people
Outliers
No Outliers
1.0
0.5




house_median_value_(dollars)

−0.8
huber
lasso
linear
ridge