Inference

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
from sklearn.preprocessing import StandardScaler
```

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

Separate Data Subsets

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

In [4]:
```
# seed for consistent splits
random.seed(1636)

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

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

# 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])

# cleaned idxs
train_idxs = [idx for idx in train_all if idx not in outlier_idxs]
test_idxs = [idx for idx in test_all if idx not in outlier_idxs]
```

In [5]:
```
# get labels because these don't need to change

label = 'murder_per_100_k'
y = df[label]

y_train = y.iloc[train_idxs]
y_test = y.iloc[test_idxs]

print('Train Len:\t {} \nTest Len:\t {}'.format(len(y_train),len(y_test)))
```

```
Train Len:       640
Test Len:        276
```

In [6]:
```
# drop irrelevant columns
x_features_df = df.drop(['MSA_orig', 'MSA_corr', 'MSA_abbr', 'murder_per_100_k'], axis=1)

# standardize, fitting only on training rows
standardizer = StandardScaler().fit(x_features_df.iloc[train_idxs])
x_features = pd.DataFrame(standardizer.transform(x_features_df), columns=x_features_df.columns)

# train test split
x_train = x_features.iloc[train_idxs]
x_test = x_features.iloc[test_idxs]

print('Train X and y match: {}'.format(len(x_train)==len(y_train)))
print('Test  X and y match: {}'.format(len(x_test)==len(y_test)))
print('\nNumber of Predictors: {}'.format(len(x_train.columns)))

print('\nFEATURE NAMES:')
for name in x_train.columns:
    print(' -'+name)
```

```
Train X and y match: True
Test  X and y match: True

Number of Predictors: 9

FEATURE NAMES:
 -year
 -now_married_except_separated
 -less_than_high_school_diploma
 -unmarried_portion_of_women_15_to_50_years_who_had_a_birth_in_past_12_months
 -households_with_food_stamp_snap_benefits
 -percentage_married-couple_family
 -percentage_female_householder_no_husband_present_family
 -poverty_all_people
 -house_median_value_(dollars)
```

Fitting The Models

In [7]:
```
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
```

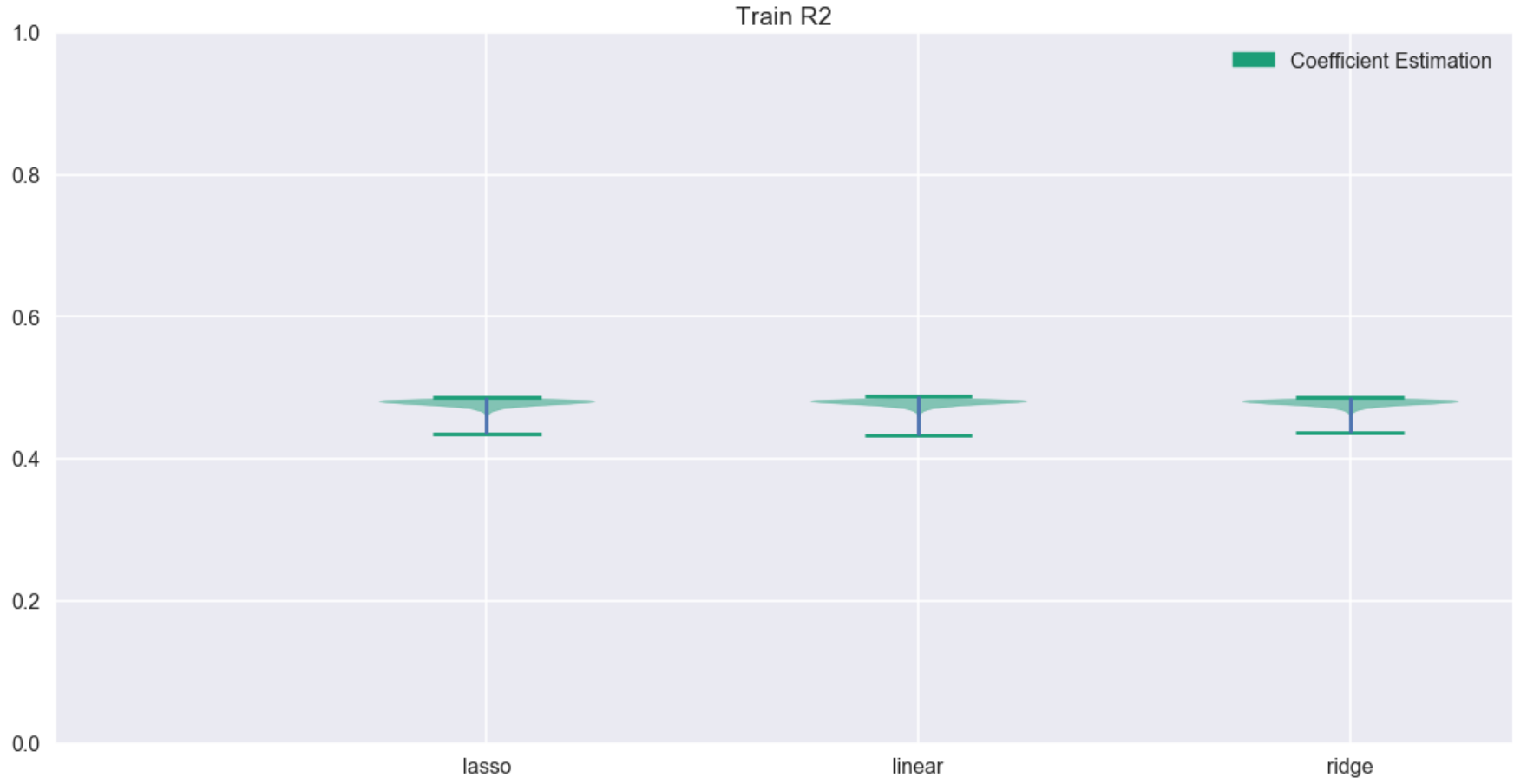
In [14]:
```
# instantiate and fit models
def make_models(x_train, y_train):
    md = dict()

    md['linear'] = LinearRegression().fit(x_train, y_train)
    md['ridge'] = RidgeCV(cv=5).fit(x_train, y_train)
    md['lasso'] = LassoCV(cv=5).fit(x_train, y_train)

    return md
```

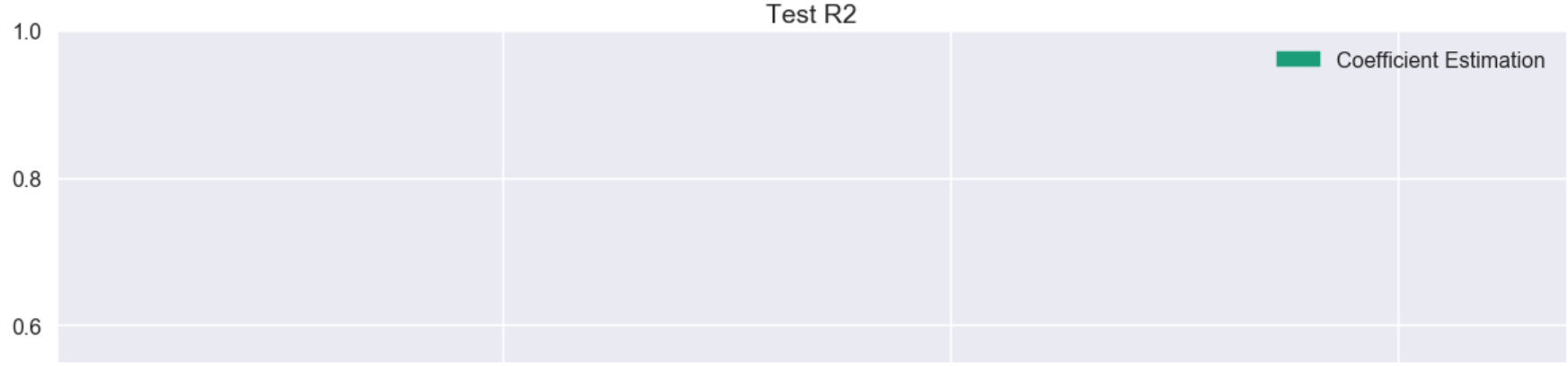
In [18]:
```
# run the model to estimate parameters

exp_1 = run_experiment(make_models, 10000, x_train, y_train, x_test, y_test, coeff_names=x_train.col
print('Done')
```

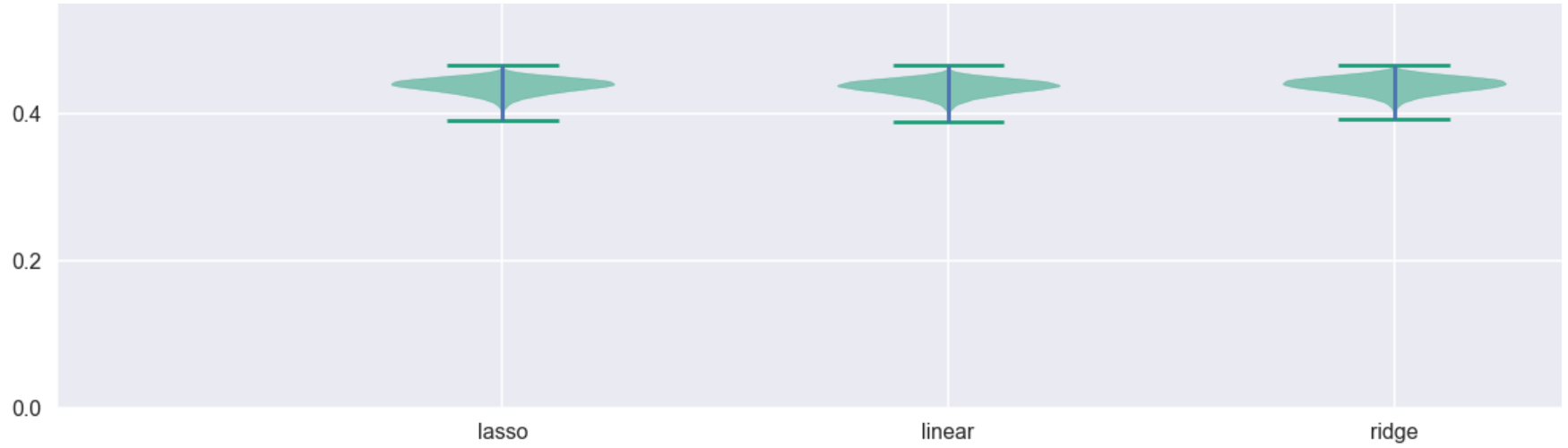
```
Done
```

Accuracy Results

In [21]:
```
violin_plots(exp_1, ['Train R2','Test R2'], experiment_name='Coefficient Estimation', center_zero=Fa
```

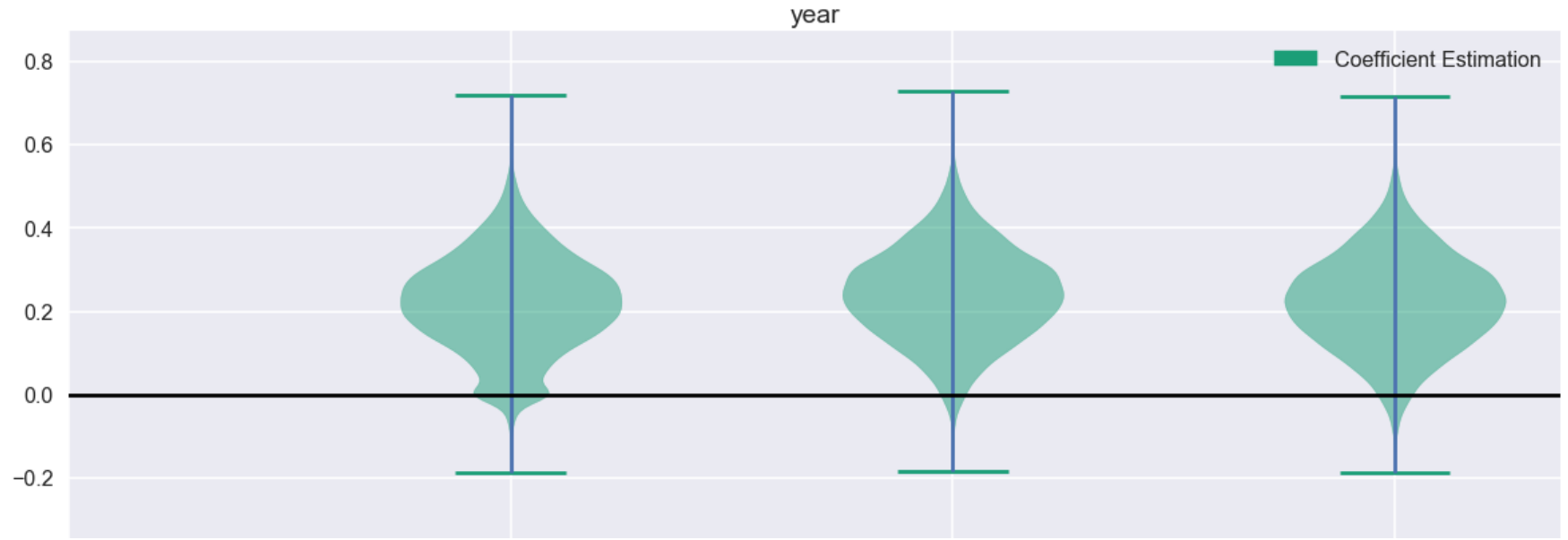

Train R2
Coefficient Estimation
1.0
0.8
0.6
0.4
0.2
0.0
lasso
linear
ridge

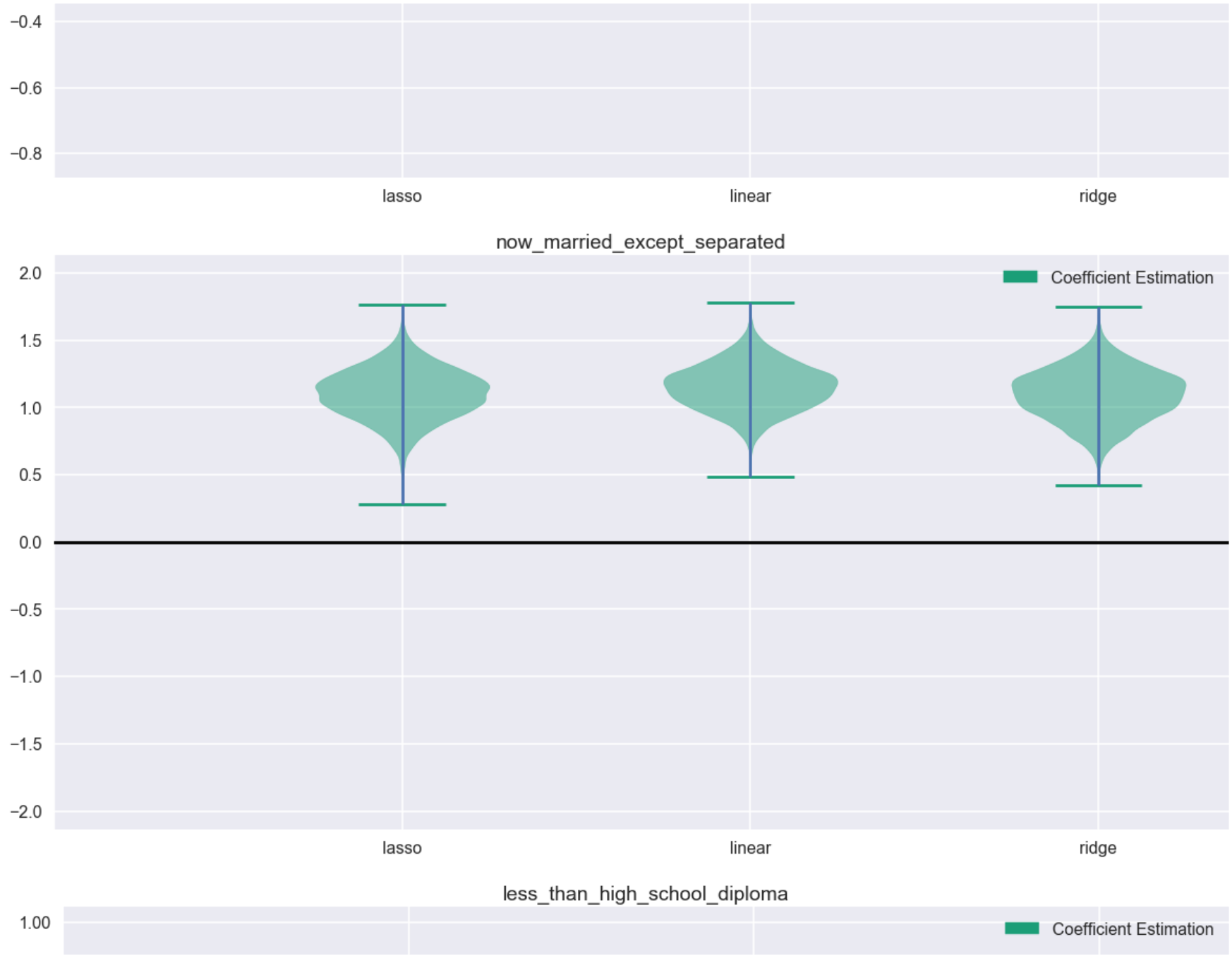

Test R2
Coefficient Estimation
1.0
0.8
0.6

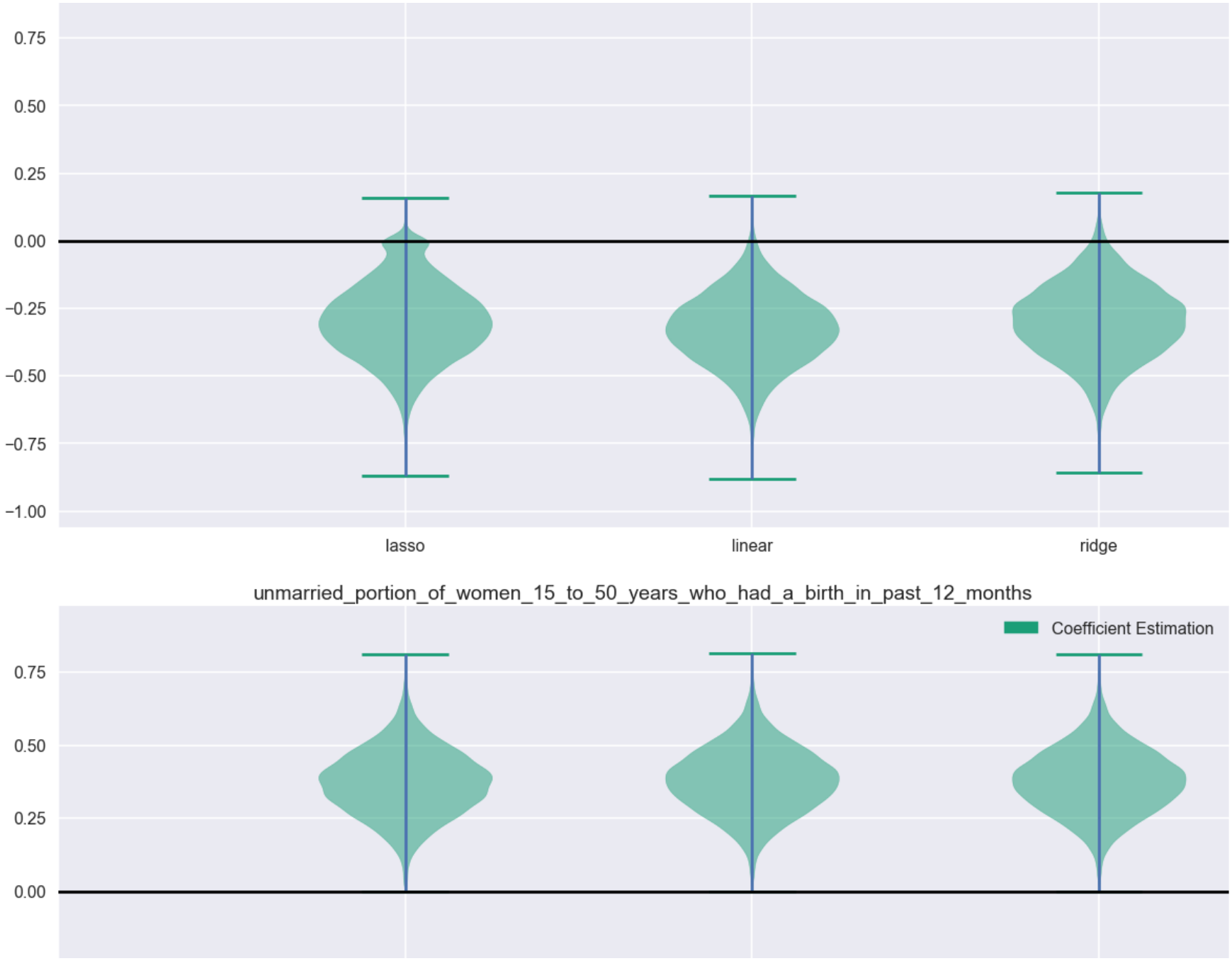


Confidence Results

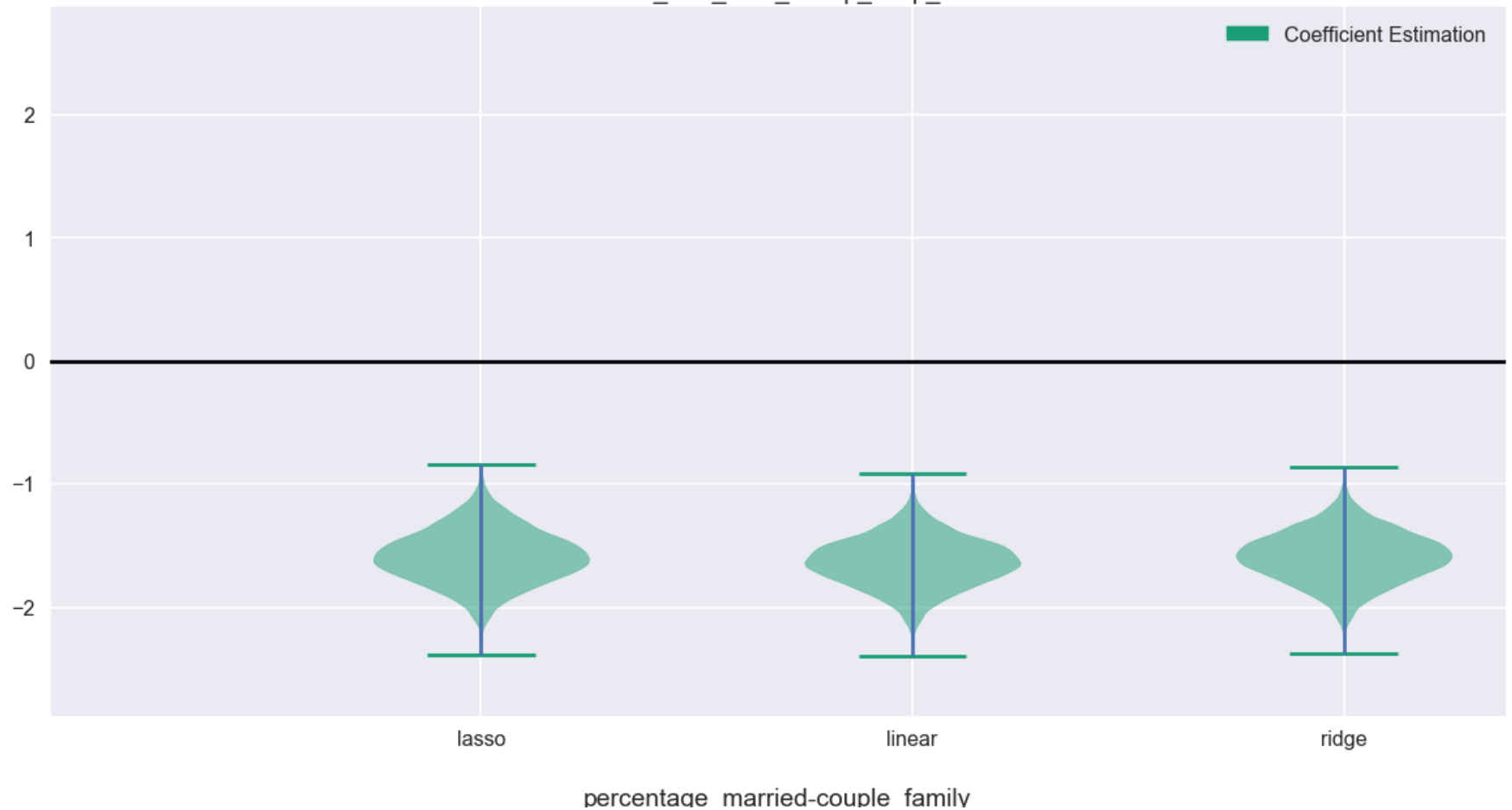
In [22]:
```
violin_plots(exp_1, x_train.columns, experiment_name='Coefficient Estimation')
```



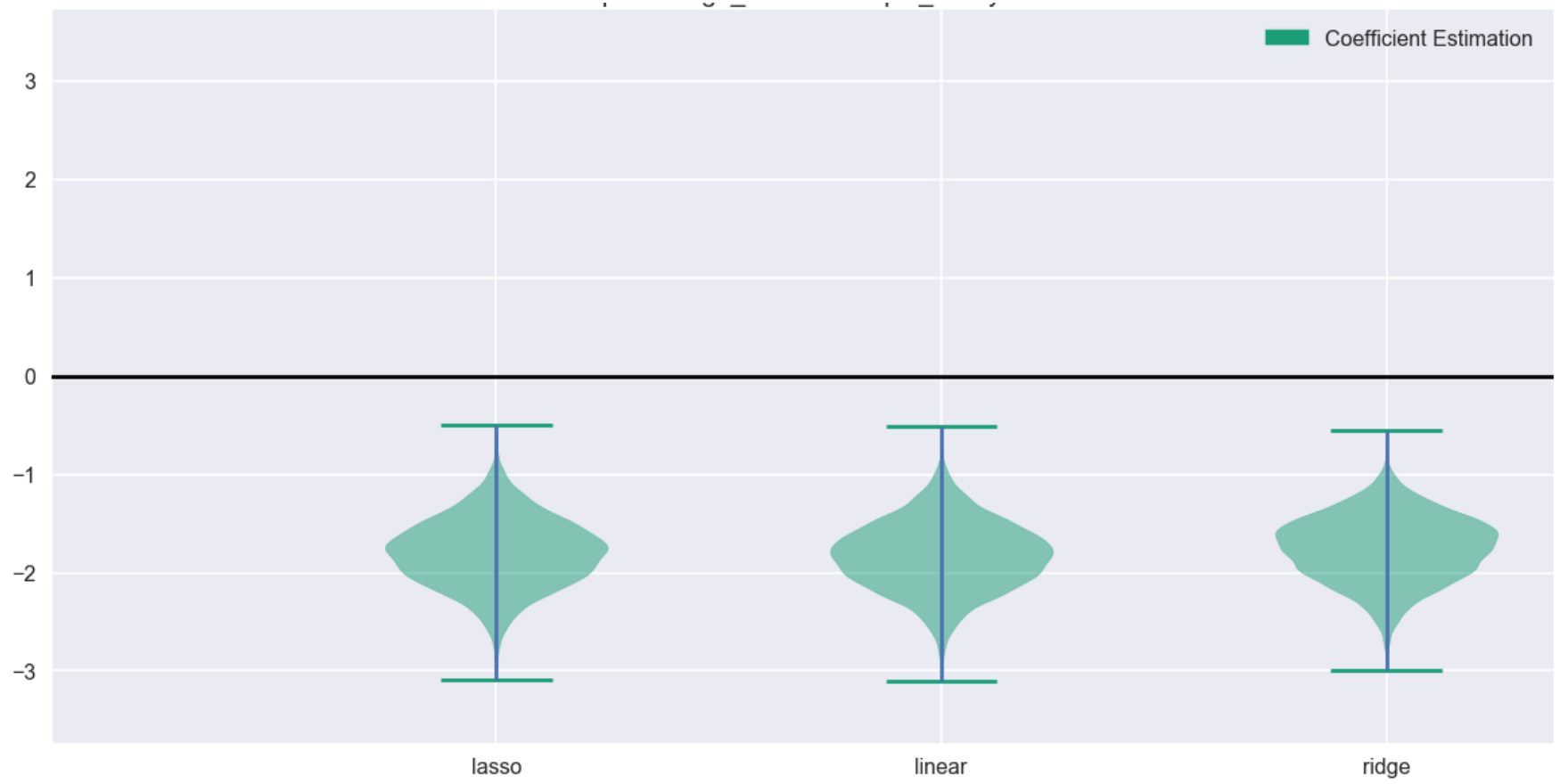

−0.4
−0.6
−0.8
lasso
linear
ridge
now_married_except_separated
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
Coefficient Estimation
lasso
linear
ridge
less_than_high_school_diploma
1.00
Coefficient Estimation

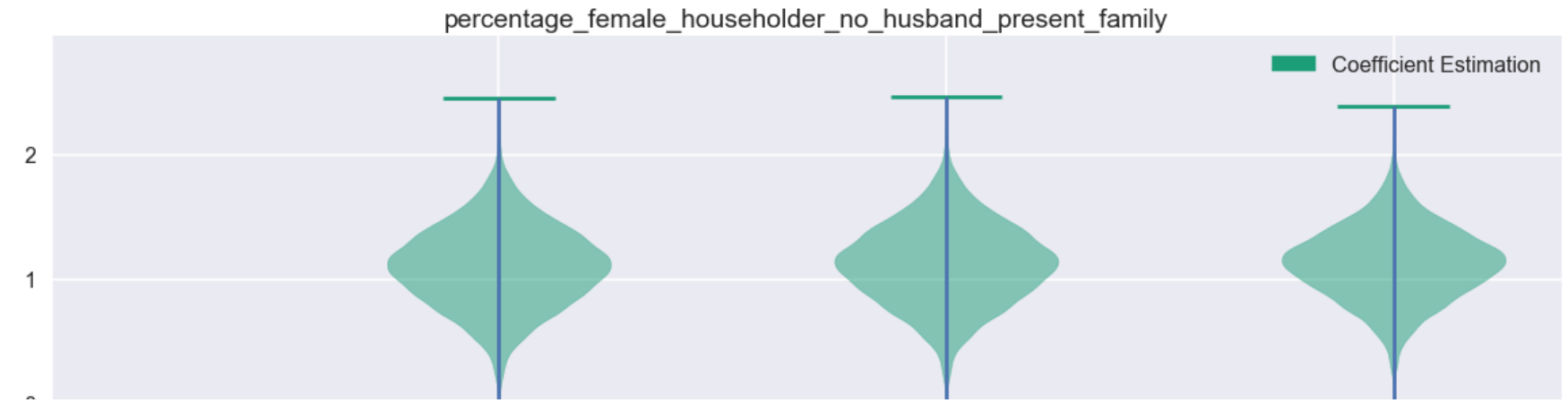

0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
lasso
linear
ridge
unmarried_portion_of_women_15_to_50_years_who_had_a_birth_in_past_12_months
Coefficient Estimation
0.75
0.50
0.25
0.00

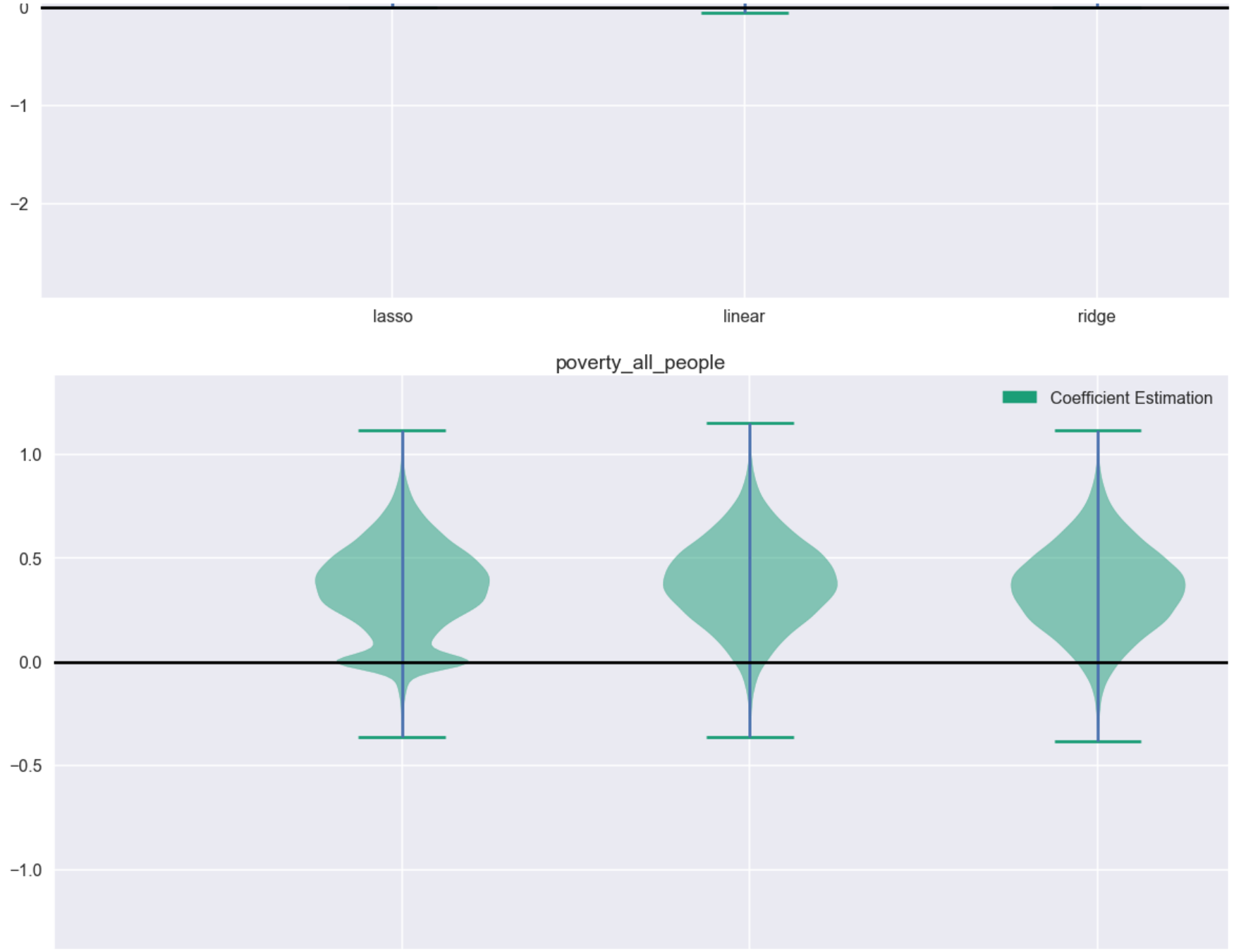
households_with_food_stamp_snap_benefits

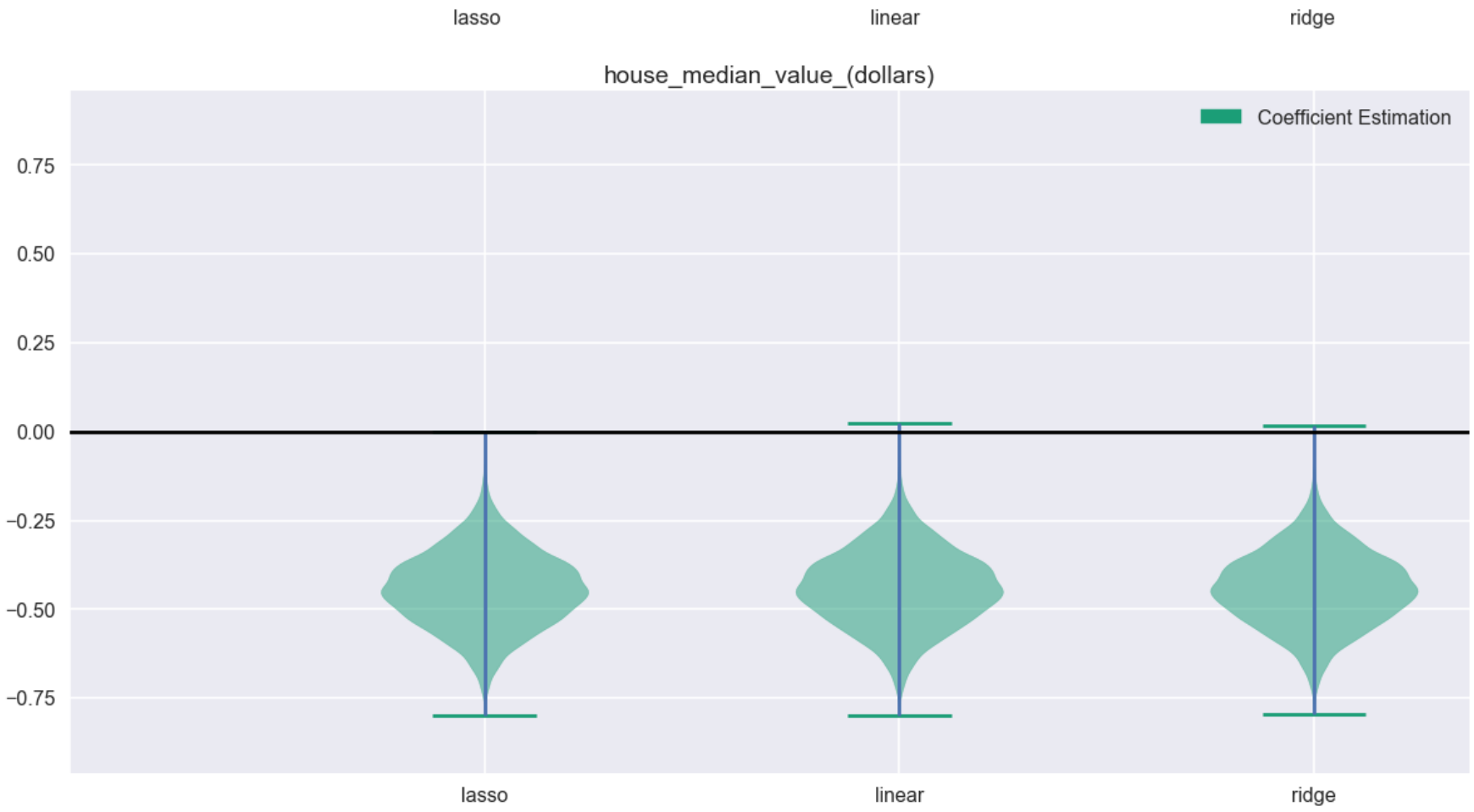


percentage_married-couple_family


Coefficient Estimation
3
2
1
0
−1
−2
−3
lasso
linear
ridge


percentage_female_householder_no_husband_present_family
Coefficient Estimation
2
1


0
−1
−2
lasso
linear
ridge
poverty_all_people
Coefficient Estimation
1.0
0.5
0.0
−0.5
−1.0


lasso
linear
ridge
house_median_value_(dollars)
Coefficient Estimation
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
lasso
linear
ridge