

In [50]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import geopandas as gpd
from shapely.geometry import Point, Polygon
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
```

The goal of this project is to see if there is a correlation between the amount of funding states spend on educational programs and average SAT scores.

In [51]:

```
file_list_1 = "funding.xlsx"
```

In [52]:

```
funding = pd.read_excel(file_list_1)
```

In [53]:

```
funding.head()
```

Out[53]:

	Year	State	Total Funding for Edu Programs	Number of Public Schools
0	2018	Alabama	565131682	1637
1	2018	Alaska	294369044	509
2	2018	Arizona	911138789	2267
3	2018	Arkansas	361359980	1102
4	2018	California	4356198454	9177

Below I created a new column "Funding per School" to negate the issue of varrying populations between states.

In [54]:

```
funding['Funding per School'] = funding['Total Funding for Edu Programs']/funding['Number of Public Schools']
```

In [55]:

```
funding.head()
```

Out[55]:

	Year	State	Total Funding for Edu Programs	Number of Public Schools	Funding per School
0	2018	Alabama	565131682	1637	345223.996335
1	2018	Alaska	294369044	509	578328.180747
2	2018	Arizona	911138789	2267	401913.890163
3	2018	Arkansas	361359980	1102	327912.867514
4	2018	California	4356198454	9177	474686.548327

Below I calculated the percent change. The percent change in this context indicates either the amount of increase or decrease in funding by state between 2017 and 2018.

In [78]:

```
funding_2018, funding_2017 = [funding[funding['Year']==y].sort_values(by=['State'  
, axis = 0).reset_index(drop=True)  
                               for y in funding['Year'].unique()]
```

In [79]:

```
funding_2017['Percent_Change'] = ((funding_2018['Funding per School']-funding_20  
17['Funding per School']) /  
                                funding_2017['Funding per School'])*100
```

In [80]:

```
funding_change = funding_2017[['State', 'Percent_Change']]
```


In [86]:

```
SAT_2017['Percent_Change'] = ((SAT_2018['Avg. Cumulative SAT Score'] - SAT_2017['Avg. Cumulative SAT Score']) / SAT_2017['Avg. Cumulative SAT Score'])*100
```

In [87]:

```
SAT_change = SAT_2017[['State', 'Percent_Change']]
```

In [88]:

```
SAT_change.head()
```

Out[88]:

	State	Percent_Change
0	Alabama	0.085837
1	Alaska	2.407407
2	Arizona	2.956989
3	Arkansas	-3.228477
4	California	1.990521

The following shapefile was pulled from <https://www.arcgis.com/home/item.html?id=f7f805eb65eb4ab787a0a3e1116ca7e5> (<https://www.arcgis.com/home/item.html?id=f7f805eb65eb4ab787a0a3e1116ca7e5>)

In [89]:

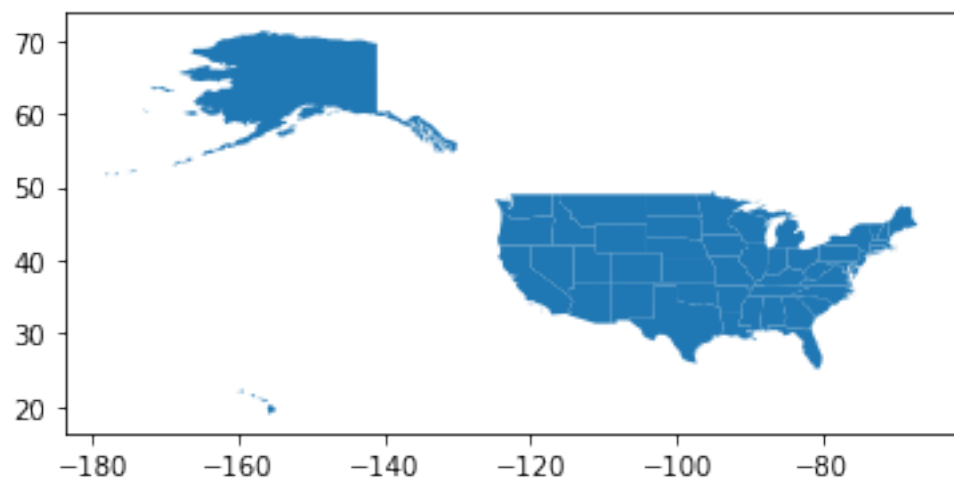
```
usa = gpd.read_file('states_21basic/states.shp')
```

In [90]:

```
usa.plot()
```

Out[90]:

<matplotlib.axes._subplots.AxesSubplot at 0x125452898>

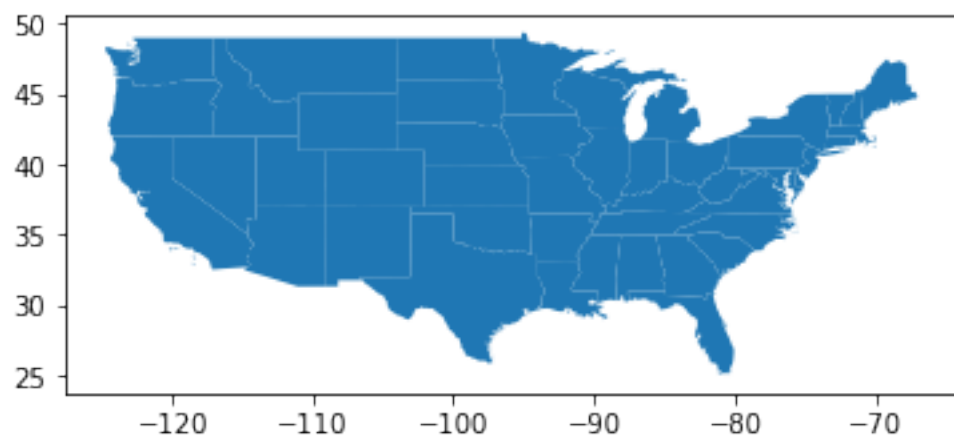


In [91]:

```
usa[usa['STATE_NAME'] != 'Alaska'][1:].plot()
```

Out[91]:

<matplotlib.axes._subplots.AxesSubplot at 0x125915198>



In [92]:

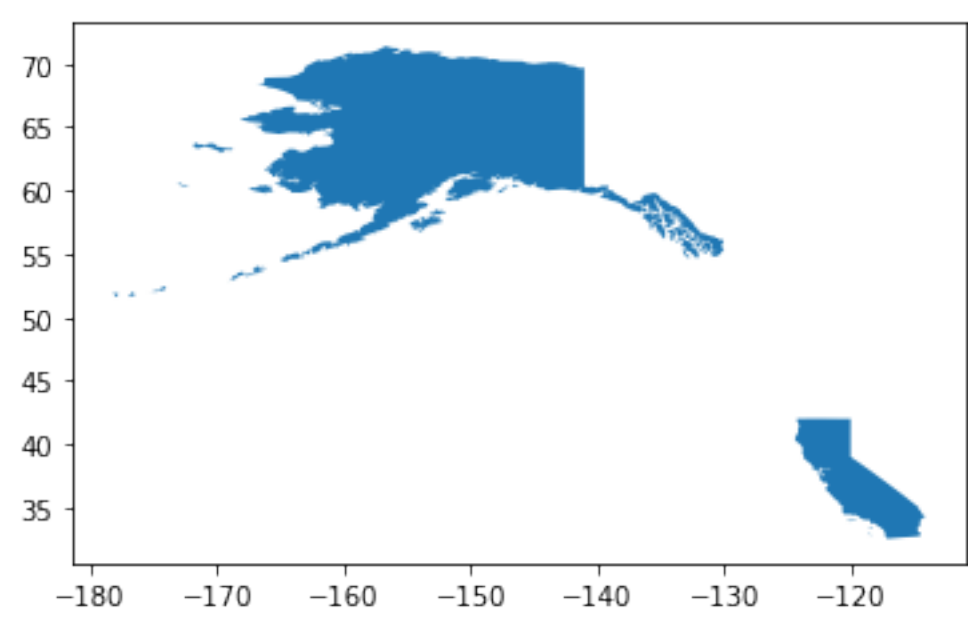
```
usa = usa.set_index('STATE_NAME')
```

In [93]:

```
usa.loc[['Alaska','California']].plot()
```

Out[93]:

<matplotlib.axes._subplots.AxesSubplot at 0x12598b780>



In [94]:

```
usa.head()
```

Out[94]:

	DRAWSEQ	STATE_FIPS	SUB_REGION	STATE_ABBR	geometry
STATE_NAME					
Hawaii	1	15	Pacific	HI	(POLYGON ((-160.0738033454681 22.0041773479577...
Washington	2	53	Pacific	WA	(POLYGON ((-122.4020153103835 48.2252163723779...
Montana	3	30	Mountain	MT	POLYGON ((-111.4754253002074 44.70216236909688...
Maine	4	23	New England	ME	(POLYGON ((-69.77727626137293 44.0741483685119...
North Dakota	5	38	West North Central	ND	POLYGON ((-98.73043728833767 45.93827137024809...

Below I created a two heat maps to demonstrate the correlation, or lack there of, between school funding and SAT scores. I choose to exclude Hawaii and Alaska.

In [95]:

```
SAT_change = SAT_change.set_index('State')  
funding_change = funding_change.set_index('State')
```

In [96]:

```
usa['sat_change'] = SAT_change['Percent_Change']  
usa['funding_change'] = funding_change['Percent_Change']
```

In [97]:

```
usa_idx = usa.index  
sat_idx = SAT_change.index  
fun_idx = funding_change.index
```

In [98]:

```
map_states = []  
for state in usa_idx:  
    if state not in ['Hawaii', 'Alaska']:  
        map_states.append(state)  
  
usa = usa.loc[map_states]  
usa = usa.dropna(how='any')
```

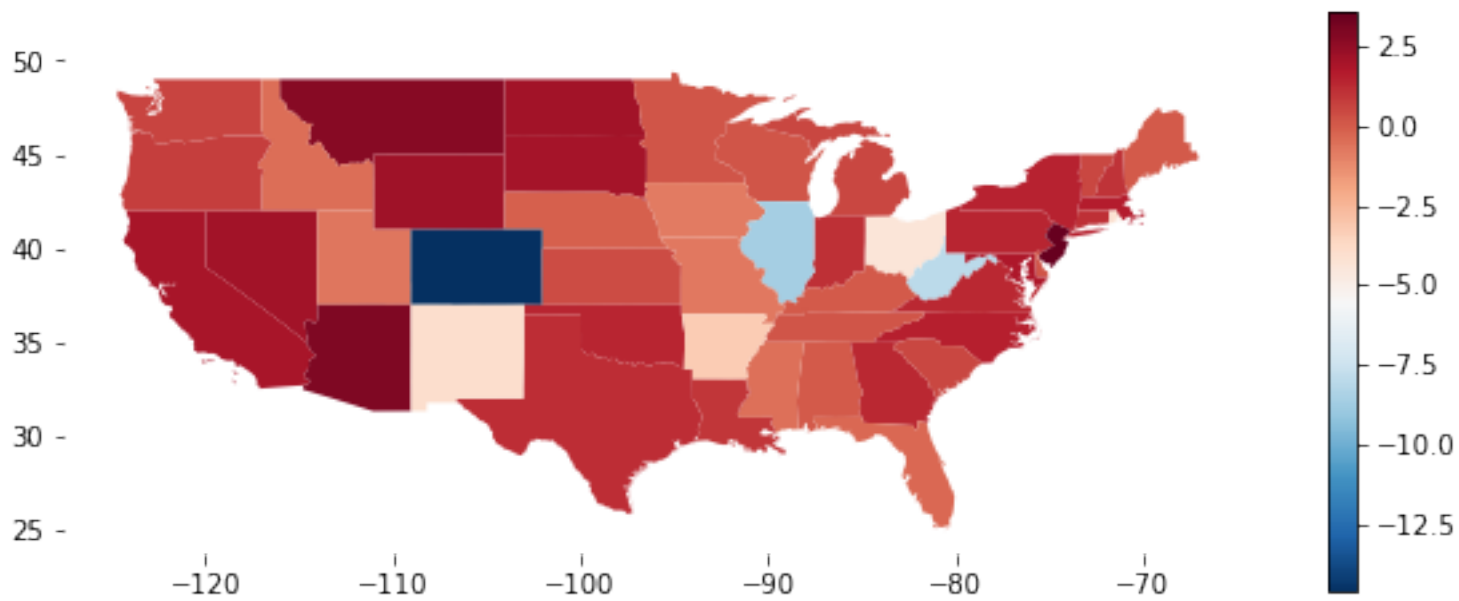
In [99]:

```
fig, ax = plt.subplots(1, 1, figsize=(10,4))

usa.plot(column='sat_change', cmap='RdBu_r', legend=True, ax=ax)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)
fig.suptitle('SAT Percent Change [2017-2018]', fontsize=20)

plt.savefig('sat')
plt.show()
```

SAT Percent Change [2017-2018]

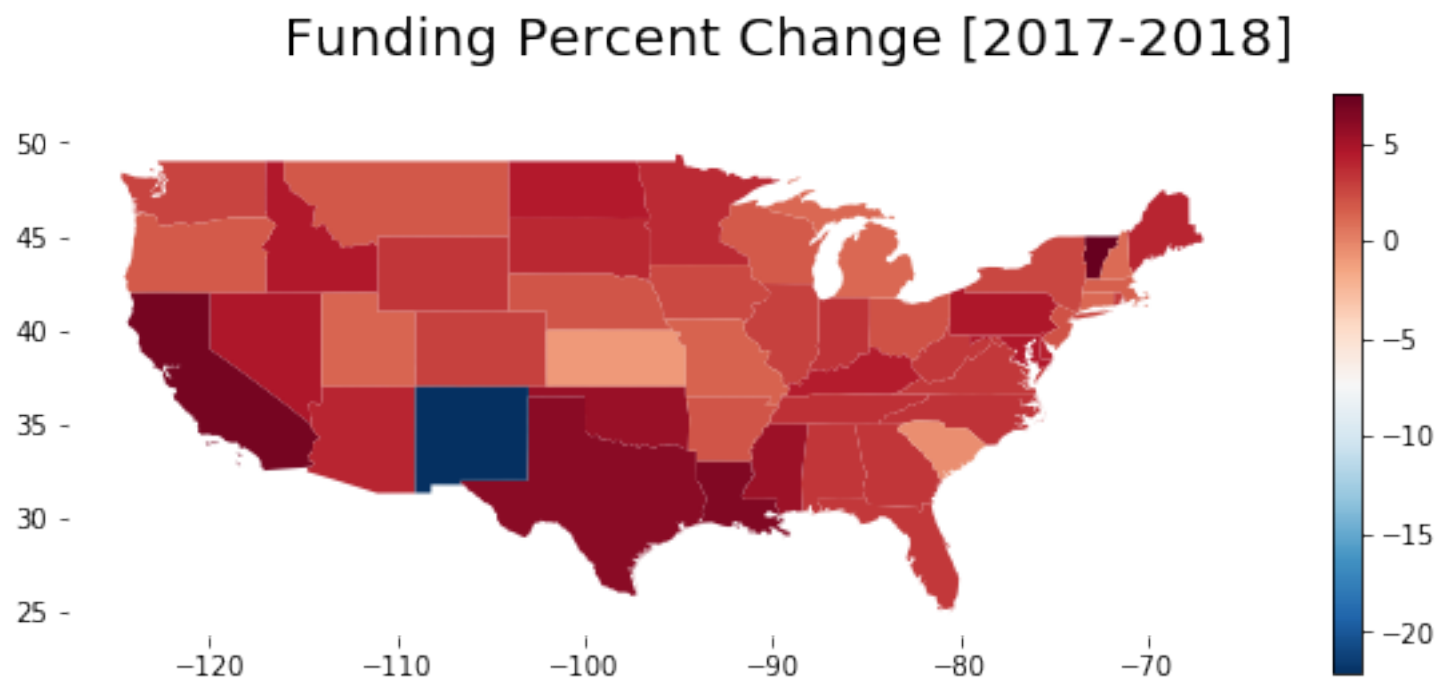



```
In [100]:
```

```
fig, ax = plt.subplots(1, 1, figsize=(10,4))

usa.plot(column='funding_change', cmap='RdBu_r', legend=True, ax=ax)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)
fig.suptitle('Funding Percent Change [2017-2018]', fontsize=20)

plt.savefig('funding')
plt.show()
```



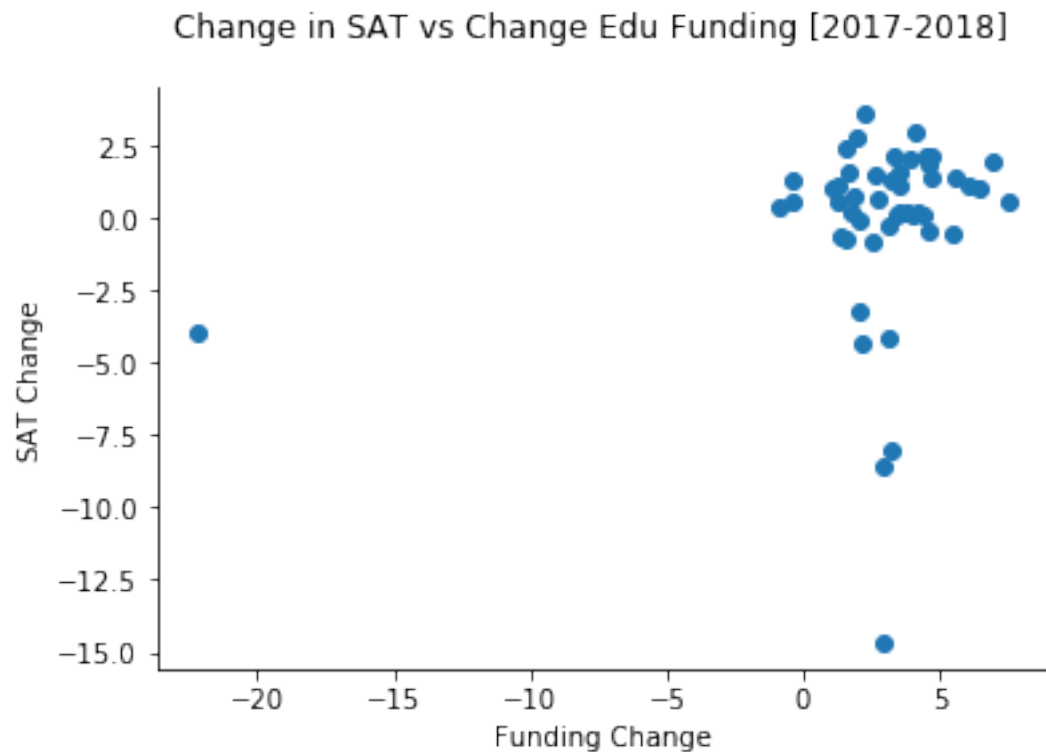
The heat maps indicate that there is not a correlation between education funding and SAT scores on the state level. To confirm this I created a scatter plot.

In [101]:

```
fig,ax = plt.subplots()

ax.scatter(funding_change, SAT_change)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
plt.xlabel('Funding Change')
plt.ylabel('SAT Change')
fig.suptitle('Change in SAT vs Change Edu Funding [2017-2018]', fontsize=12)

plt.savefig('SAT vs funding')
plt.show()
```



Below I took a more general look at the data by creating bar graphs for funding per school by region in 2017 and 2018, separately, and bar graphs for SAT scores by region in 2017 and 2018, separately (so percent change was not taken into account in the following graphs).

In [102]:

```
usa['SAT_2017'] = SAT_2017.set_index('State')['Avg. Cumulative SAT Score']
usa['SAT_2018'] = SAT_2018.set_index('State')['Avg. Cumulative SAT Score']
usa['Funding_2017'] = funding_2017.set_index('State')['Funding per School']
usa['Funding_2018'] = funding_2018.set_index('State')['Funding per School']
```

In [77]:

```
usa.head()
```

Out[77]:

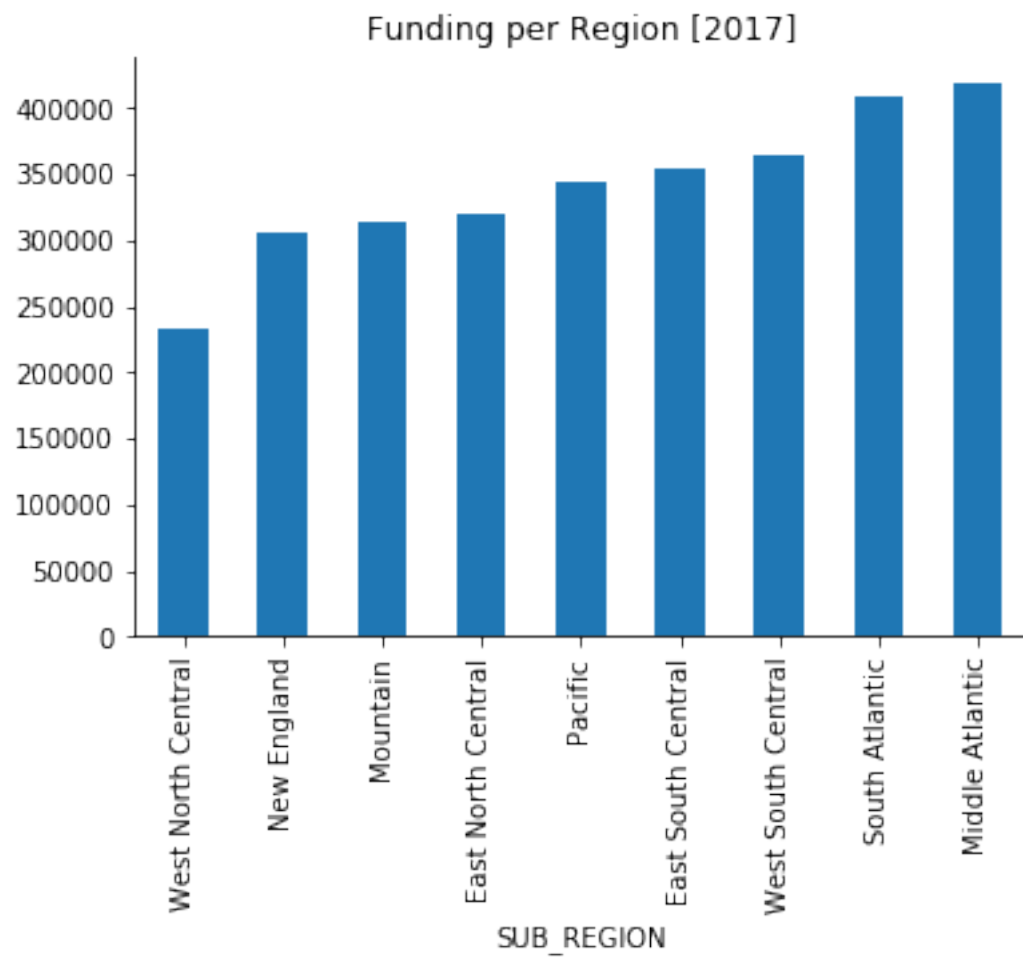
	DRAWSEQ	STATE_FIPS	SUB_REGION	STATE_ABBR	geometry	sat_
STATE_NAME						
Hawaii	1	15	Pacific	HI	((POLYGON ((-160.0738033454681 22.0041773479577...	1.
Washington	2	53	Pacific	WA	((POLYGON ((-122.4020153103835 48.2252163723779...	0.
Montana	3	30	Mountain	MT	((POLYGON ((-111.4754253002074 44.70216236909688...	2.
Maine	4	23	New England	ME	((POLYGON ((-69.77727626137293 44.0741483685119...	0.
North Dakota	5	38	West North Central	ND	((POLYGON ((-98.73043728833767 45.93827137024809...	2.

```
In [148]:
```

```
fig, ax = plt.subplots()

usa.groupby('SUB_REGION').mean()['Funding_2017'].sort_values().plot.bar(title =
'Funding per Region [2017]')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

plt.savefig('regional_funding_2017')
plt.show()
```

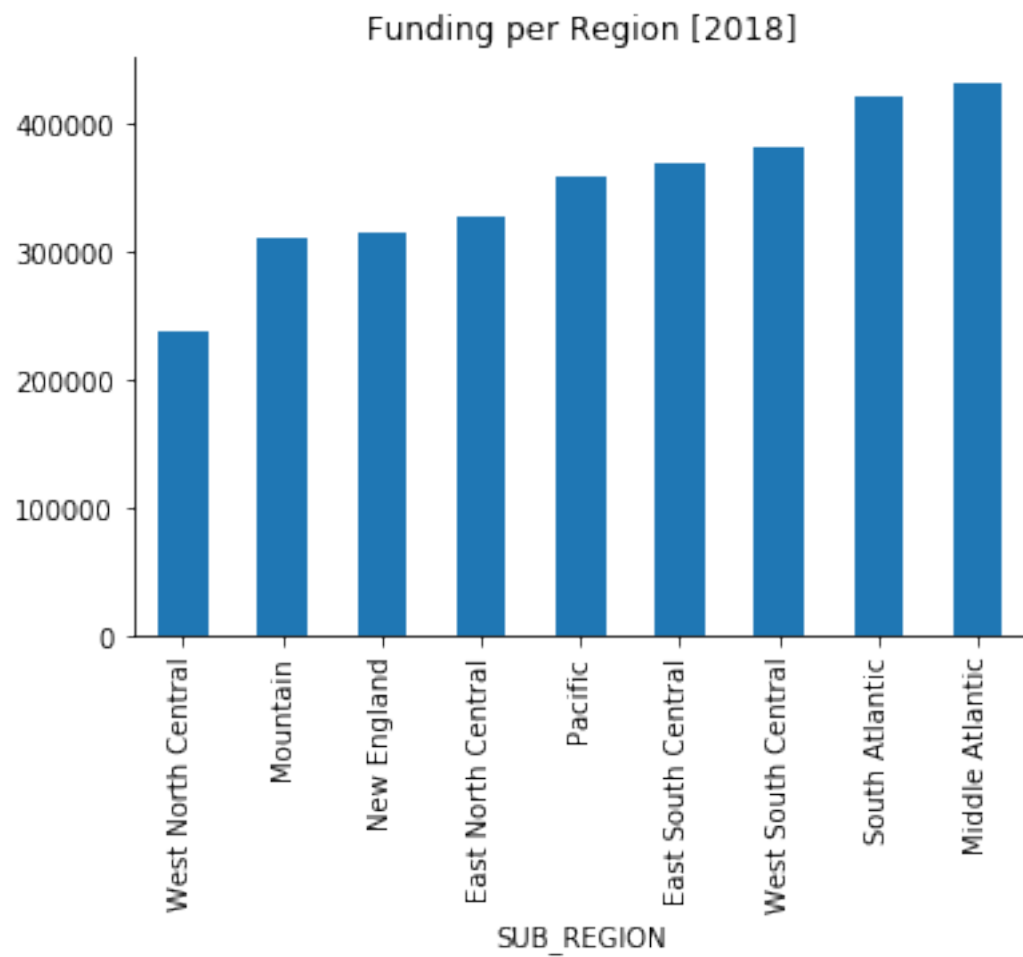


```
In [149]:
```

```
fig, ax = plt.subplots()

usa.groupby('SUB_REGION').mean()['Funding_2018'].sort_values().plot.bar(title =
'Funding per Region [2018]')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

plt.savefig('regional_funding_2018')
plt.show()
```

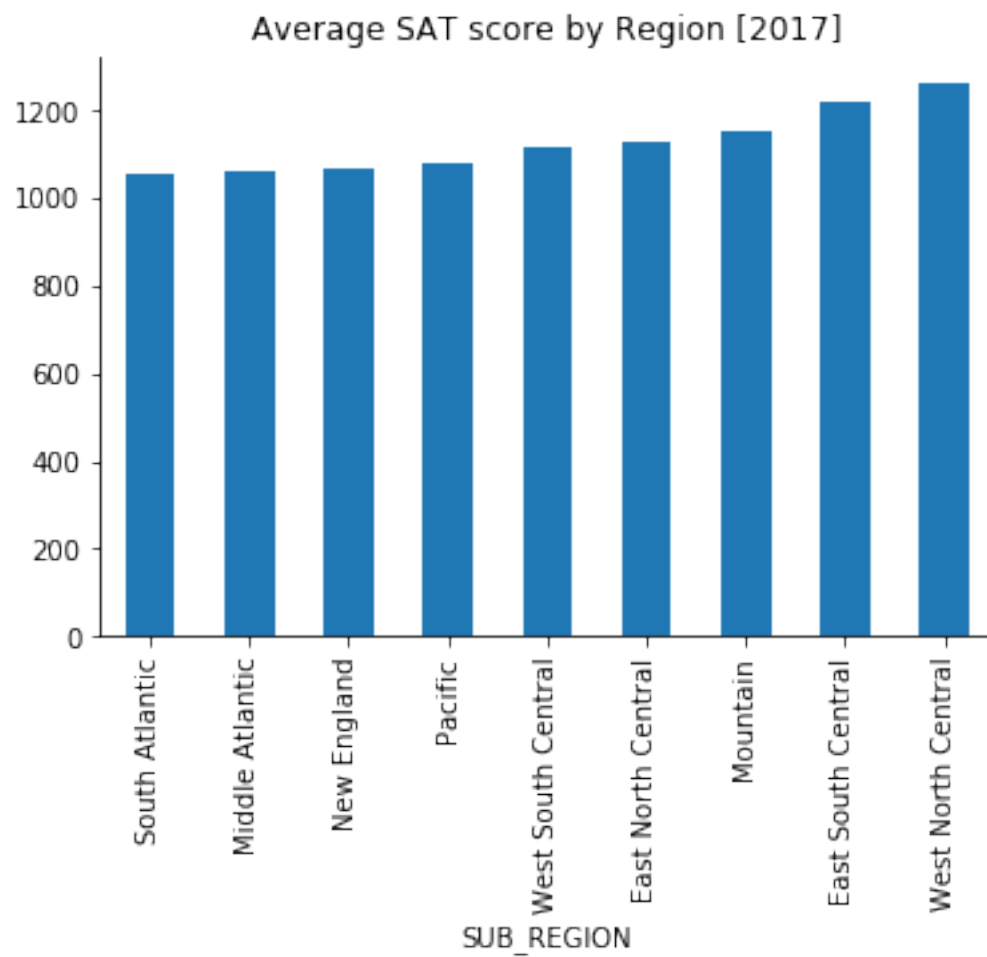


```
In [150]:
```

```
fig, ax = plt.subplots()

usa.groupby('SUB_REGION').mean()['SAT_2017'].sort_values().plot.bar(title = 'Average SAT score by Region [2017]')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

plt.savefig('avg_regional_SAT_2017')
plt.show()
```

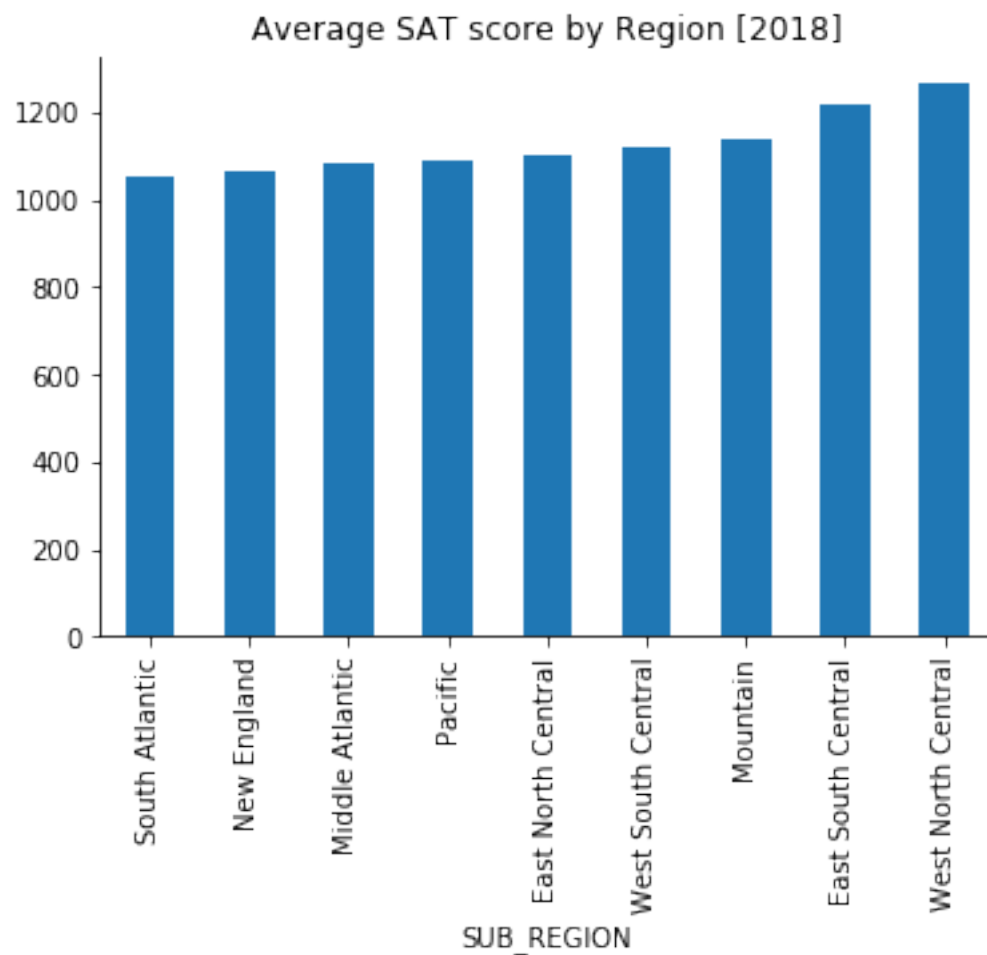


```
In [115]:
```

```
fig, ax = plt.subplots()

usa.groupby('SUB_REGION').mean()['SAT_2018'].sort_values().plot.bar(title = 'Average SAT score by Region [2018]')
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)

plt.savefig('avg_regional_SAT_2018')
plt.show()
```



From these bar graphs it may be noted that the "Middle Atlantic" region consistently received the most funding, however remained in the bottom three performance wise. This again suggest that more funding does not necessarily equate to higher test scores.