City Council Voter Turnout Analysis

We examine the change in voter turnout over the various CC election years.
Here, we are answering an essential question: **How has voter turnout by precinct changed across election year?**

In [2]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

#loading datasets into dataframes
cc2011 = pd.read_csv("2011_CityCouncil_Results_Race_Turnout.csv")
cc2013 = pd.read_csv("2013_CityCouncil_Race_Turnout_Results.csv")
cc2015 = pd.read_csv("2015_city_council.csv")
cc2017 = pd.read_csv("2017_CityCouncil_AtLarge_Turnout_Race.csv")
cc2019 = pd.read_csv("2019_CityCouncil_Race Turnout.csv")
```

In [3]:

```
#checking that these are all the same length
print("Shape of cc2011:", cc2011.shape)
print("Shape of cc2013:", cc2013.shape)
print("Shape of cc2015:", cc2015.shape)
print("Shape of cc2017:", cc2017.shape)
print("Shape of cc2019:", cc2019.shape)
```

```
Shape of cc2011: (254, 48)
Shape of cc2013: (254, 46)
Shape of cc2015: (254, 47)
Shape of cc2017: (254, 54)
Shape of cc2019: (257, 51)
```

In [4]:

```
cc2011 = cc2011.drop([253])
cc2011
```

Out[4]:

	Unnamed: 0	WILL DORCENA	AYANNA PRESSLEY	FELIX G ARROYO	JOHN R CONNOLLY	MICHAEL F FLAHERTY	STEPHEN J MURPHY	SEAN H RYAN	WILL FEEG Writ
0	0	16	113	111	117	100	99	24	
1	1	9	44	55	42	70	52	10	
2	2	40	133	155	123	101	109	34	
3	3	5	29	47	40	45	43	8	
4	4	12	54	67	63	69	63	11	
...	...	...	...	...	...	...	...	...	
248	248	16	71	88	90	75	72	18	
249	249	18	75	86	75	60	55	17	
250	250	32	123	126	112	99	119	30	

	Unnamed: 0	WILL DORCENA	AYANNA PRESSLEY	FELIX G ARROYO	JOHN R CONNOLLY	MICHAEL F FLAHERTY	STEPHEN J MURPHY	SEAN H RYAN	WILL FEEG Writ
251	251	11	66	74	84	52	77	12	
252	252	22	60	79	79	86	75	23	

253 rows × 48 columns

In [5]:
```
cc2013 = cc2013.drop([253])
cc2015 = cc2015.drop([253])
cc2017 = cc2017.drop([253])
```

2019 is slightly longer than the others for some reason. We will discard 2019 for now because the data needs to be manually standarized to match the other datasets. We will also disregard WP 2213 from each of the datasets since this data is incomplete.

Adding voter turnout column to each of the datasets

In [6]:
```
#beginning with 2011, add turnout column
cc2011["Turnout2011"] = cc2011["BALLOTS CAST"]/cc2011["Registered Voters"]
cc2011["Turnout2011"]
```

Out[6]:
```
0      0.186715
1      0.145342
2      0.156431
3      0.175182
4      0.140314
         ...
248    0.116996
249    0.096774
250    0.136968
251    0.127363
252    0.155075
Name: Turnout2011, Length: 253, dtype: float64
```

In [7]:
```
# adding turnout column to 2013
cc2013["Turnout2013"] = cc2013["BALLOTS CAST"]/cc2013["Registered Voters"]
cc2013["Turnout2013"]
```

Out[7]:
```
0      0.520227
1      0.453782
2      0.439695
3      0.441221
4      0.425512
         ...
248    0.318999
249    0.265783
250    0.355091
251    0.338967
252    0.323427
Name: Turnout2013, Length: 253, dtype: float64
```

In [8]:
```
# adding turnout column to 2015
cc2015["Turnout2015"] = cc2015["BALLOTS CAST"]/cc2015["Registered Voters"]
```

```
cc2015["Turnout2015"]
```

Out[8]:
```
0      0.135303
1      0.112750
2      0.134523
3      0.089686
4      0.077748
         ...
248    0.091053
249    0.075243
250    0.113333
251    0.108798
252    0.118353
Name: Turnout2015, Length: 253, dtype: float64
```

In [9]:
```
# 2017 already has a turnout column for some reason
cc2017 = cc2017.rename(columns= {"Turnout":"Turnout2017"})
cc2017["Turnout2017"]
```

Out[9]:
```
0      0.354331
1      0.287923
2      0.298865
3      0.288221
4      0.282869
         ...
248    0.230109
249    0.213855
250    0.268729
251    0.254563
252    0.236667
Name: Turnout2017, Length: 253, dtype: float64
```

Creating a DataFrame with each of the voter turnouts

In [10]:
```
# creating a new dataframe with turnout data
temp1 = cc2011[["WP", "Turnout2011"]]
turnouts = temp1.join(cc2013[["Turnout2013"]]).join(cc2015[["Turnout2015"]]).joi
turnouts
```

Out[10]:

	WP	Turnout2011	Turnout2013	Turnout2015	Turnout2017
0	101	0.186715	0.520227	0.135303	0.354331
1	102	0.145342	0.453782	0.112750	0.287923
2	103	0.156431	0.439695	0.134523	0.298865
3	104	0.175182	0.441221	0.089686	0.288221
4	105	0.140314	0.425512	0.077748	0.282869
...	...	...	...	...	...
248	2208	0.116996	0.318999	0.091053	0.230109
249	2209	0.096774	0.265783	0.075243	0.213855
250	2210	0.136968	0.355091	0.113333	0.268729
251	2211	0.127363	0.338967	0.108798	0.254563
252	2212	0.155075	0.323427	0.118353	0.236667

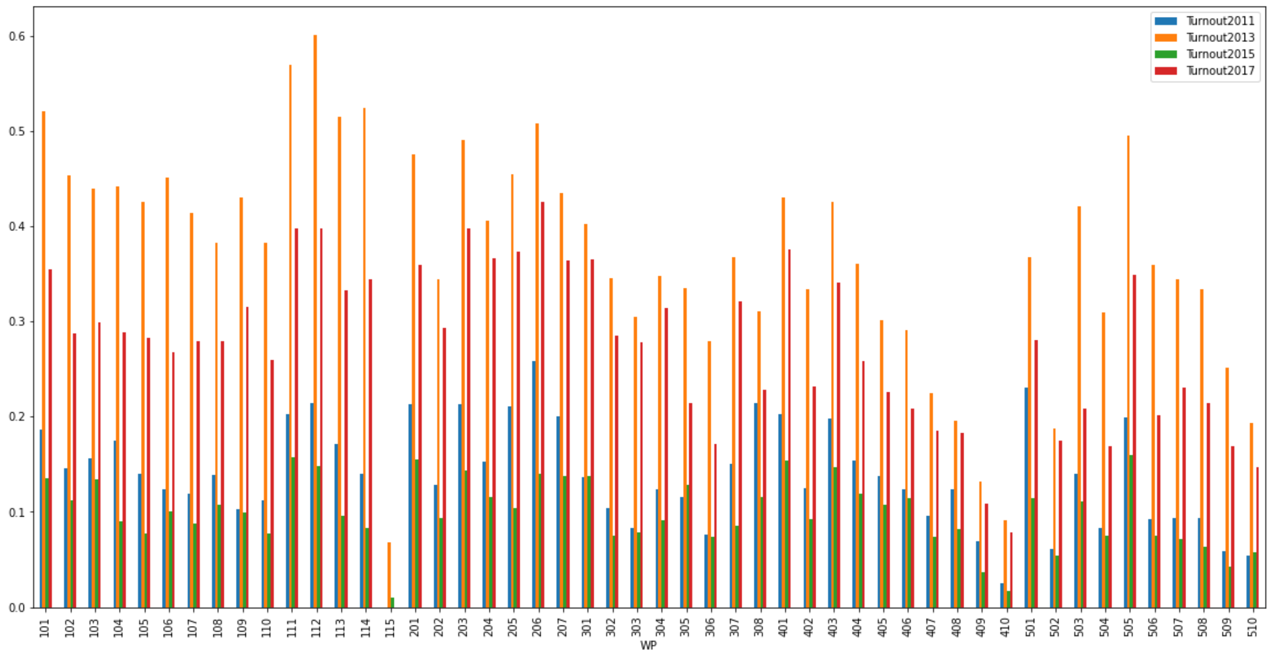
253 rows × 5 columns

Visualizing the voter turnout across election year for each precinct.

In [11]:

```
# visualizing our datasets 50 WPs at a time
turnouts[:50].plot(x="WP", y=["Turnout2011", "Turnout2013", "Turnout2015", "Turn
```

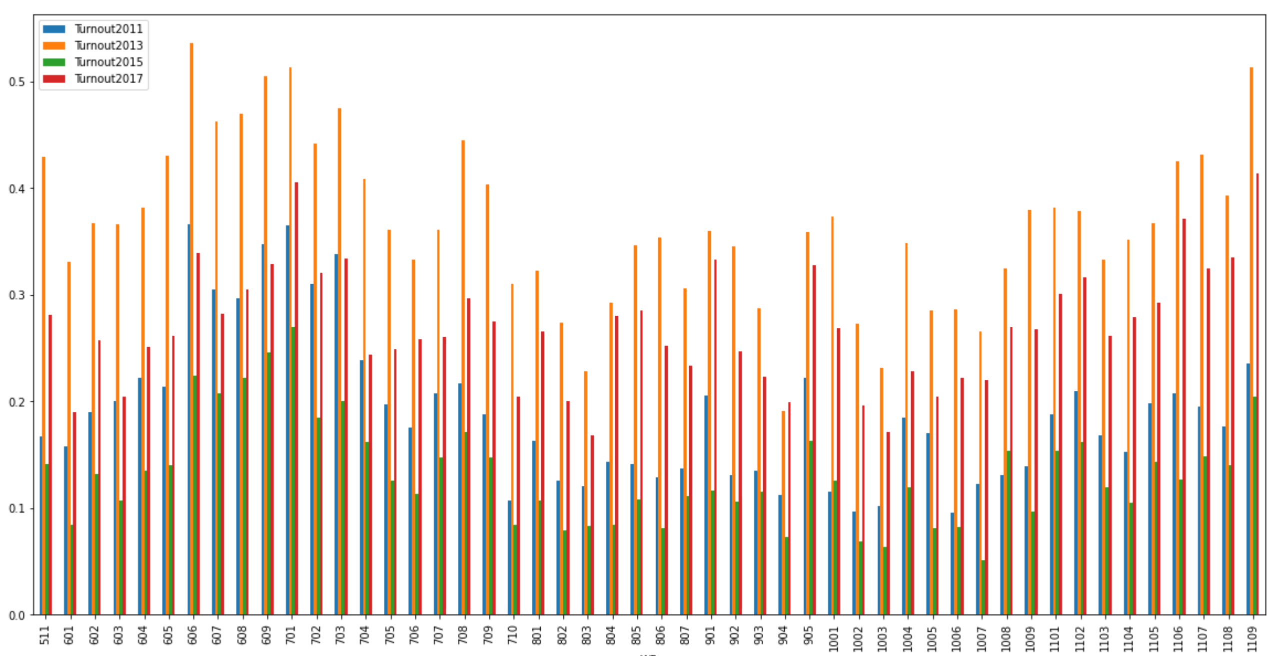
Out[11]: <AxesSubplot:xlabel='WP'>



In [12]:

```
turnouts[50:100].plot(x="WP", y=["Turnout2011", "Turnout2013", "Turnout2015", "T
```

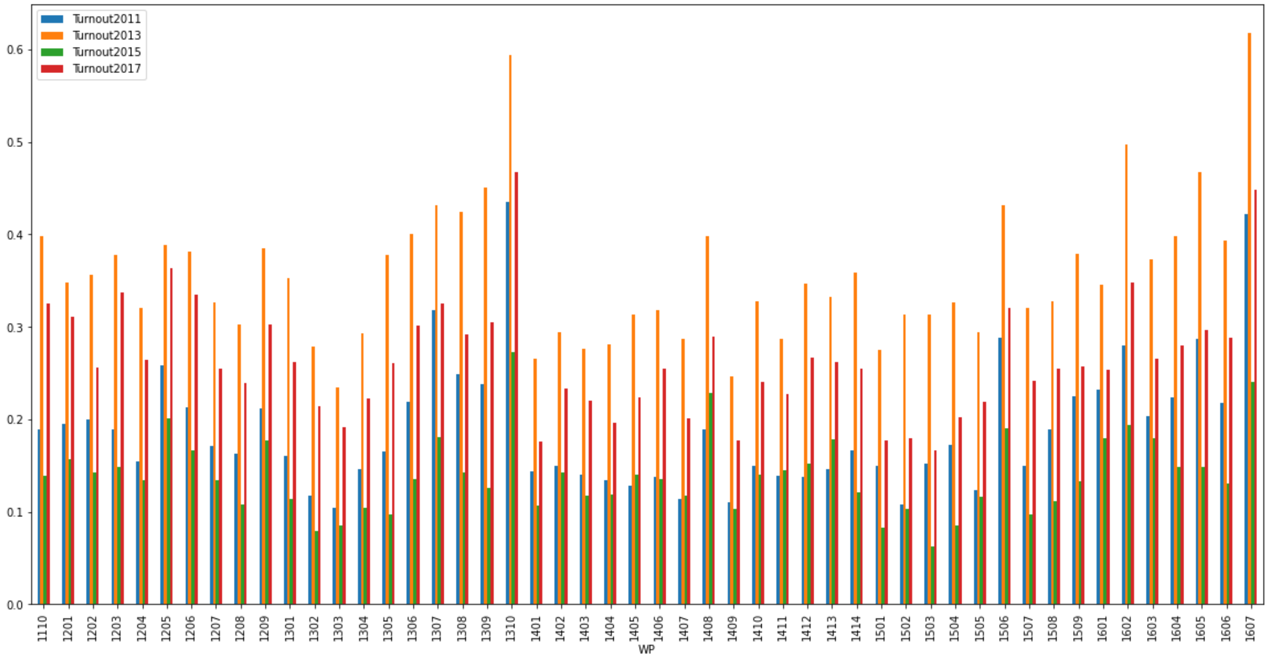
Out[12]: <AxesSubplot:xlabel='WP'>



In [13]:

```
turnouts[100:150].plot(x="WP", y=["Turnout2011", "Turnout2013", "Turnout2015", "
```

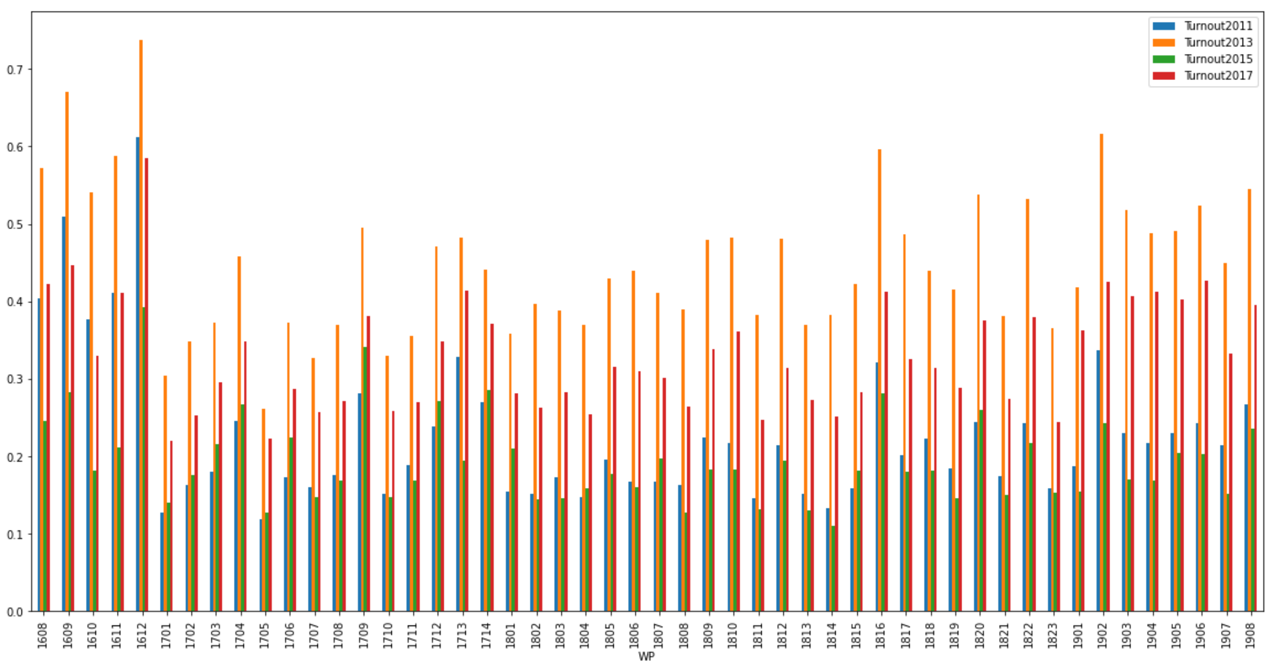
Out[13]: <AxesSubplot:xlabel='WP'>



In [14]:

```
turnouts[150:200].plot(x="WP", y=["Turnout2011", "Turnout2013", "Turnout2015", "
```

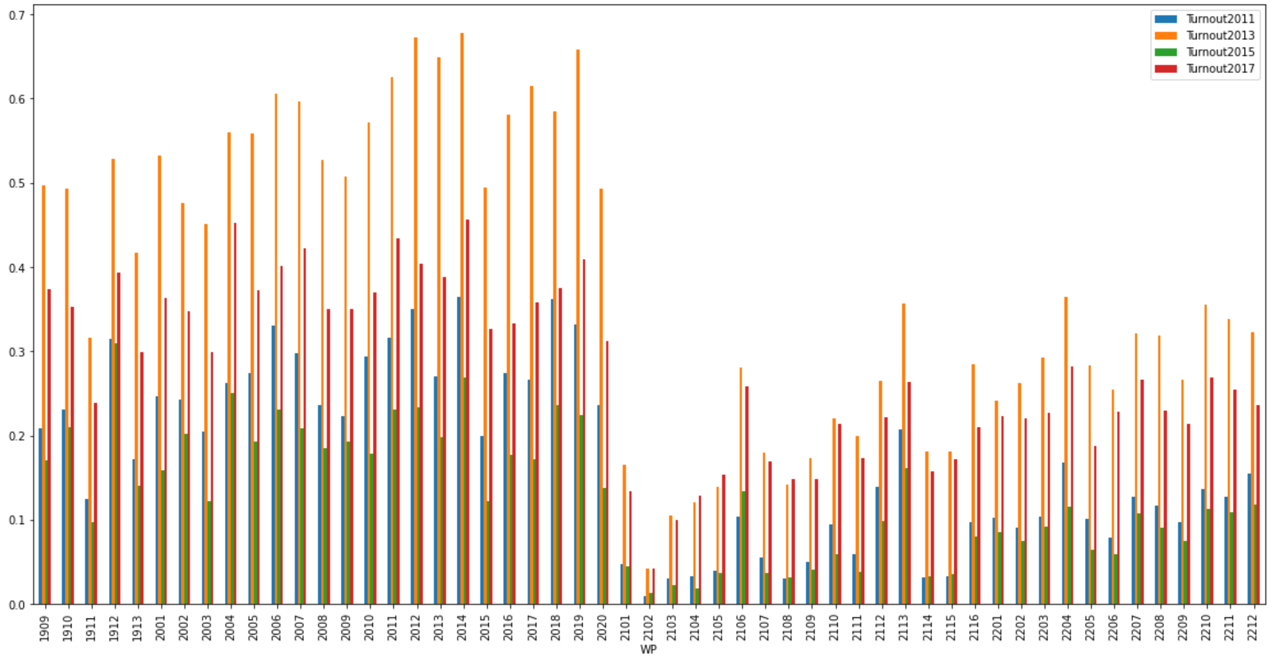
Out[14]: <AxesSubplot:xlabel='WP'>



In [15]:

```
turnouts[200:].plot(x="WP", y=["Turnout2011", "Turnout2013", "Turnout2015", "Tur
```

Out[15]: <AxesSubplot:xlabel='WP'>



The 2013 race seems to have the highest voter turnout. Why is this?

Calculating the mean voter turnout for each election year

In [16]:
```
print("Mean voter turnout 2011:", turnouts["Turnout2011"].mean())
print("Mean voter turnout 2013:", turnouts["Turnout2013"].mean())
print("Mean voter turnout 2015:", turnouts["Turnout2015"].mean())
print("Mean voter turnout 2017:", turnouts["Turnout2017"].mean())
```

```
Mean voter turnout 2011: 0.1831009593793309
Mean voter turnout 2013: 0.38535490630415914
Mean voter turnout 2015: 0.13896689236058474
Mean voter turnout 2017: 0.2825747138559744
```

As we can see, 2013 has the highest average voter turnout.

Calculating the median voter turnout for each election year

In [17]:
```
print("Median voter turnout 2011:", turnouts["Turnout2011"].median())
print("Median voter turnout 2013:", turnouts["Turnout2013"].median())
print("Median voter turnout 2015:", turnouts["Turnout2015"].median())
print("Median voter turnout 2017:", turnouts["Turnout2017"].median())
```

```
Median voter turnout 2011: 0.1702325581395349
Median voter turnout 2013: 0.3733528550512445
Median voter turnout 2015: 0.13530326594090203
Median voter turnout 2017: 0.27836192584394
```

Again, 2013 is the highest.

Calculating average change over time

In [18]:
```
import math
turnouts["Diff11_13"] = turnouts["Turnout2011"] - turnouts["Turnout2013"]
turnouts["Diff11_13"] = turnouts["Diff11_13"].abs()
turnouts["Diff13_15"] = turnouts["Turnout2013"] - turnouts["Turnout2015"]
turnouts["Diff13_15"] = turnouts["Diff13_15"].abs()
turnouts["Diff15_17"] = turnouts["Turnout2015"] - turnouts["Turnout2017"]
```

```
turnouts["Diff15_17"] = turnouts["Diff15_17"].abs()
turnouts["SumChange"] = turnouts["Diff11_13"] + turnouts["Diff13_15"] + turnouts
turnouts["AvgChange"] = turnouts["SumChange"] / 3.0
turnouts
```

Out[18]:

	WP	Turnout2011	Turnout2013	Turnout2015	Turnout2017	Diff11_13	Diff13_15	Diff15_17
0	101	0.186715	0.520227	0.135303	0.354331	0.333512	0.384923	0.219027
1	102	0.145342	0.453782	0.112750	0.287923	0.308440	0.341031	0.175172
2	103	0.156431	0.439695	0.134523	0.298865	0.283264	0.305172	0.164342
3	104	0.175182	0.441221	0.089686	0.288221	0.266039	0.351535	0.198534
4	105	0.140314	0.425512	0.077748	0.282869	0.285198	0.347764	0.205121
...	...	...	...	...	...	...	...	...
248	2208	0.116996	0.318999	0.091053	0.230109	0.202003	0.227946	0.139056
249	2209	0.096774	0.265783	0.075243	0.213855	0.169009	0.190541	0.138613
250	2210	0.136968	0.355091	0.113333	0.268729	0.218123	0.241758	0.155395
251	2211	0.127363	0.338967	0.108798	0.254563	0.211604	0.230169	0.145764
252	2212	0.155075	0.323427	0.118353	0.236667	0.168351	0.205073	0.118313

253 rows × 10 columns

Finding the Top 20 Precincts with the greatest average change in voter turnout.

In [19]:

```
#finding the top 20 precincts with the greatest average change
top_change = turnouts.sort_values(by=['AvgChange'])
top_change
```

Out[19]:

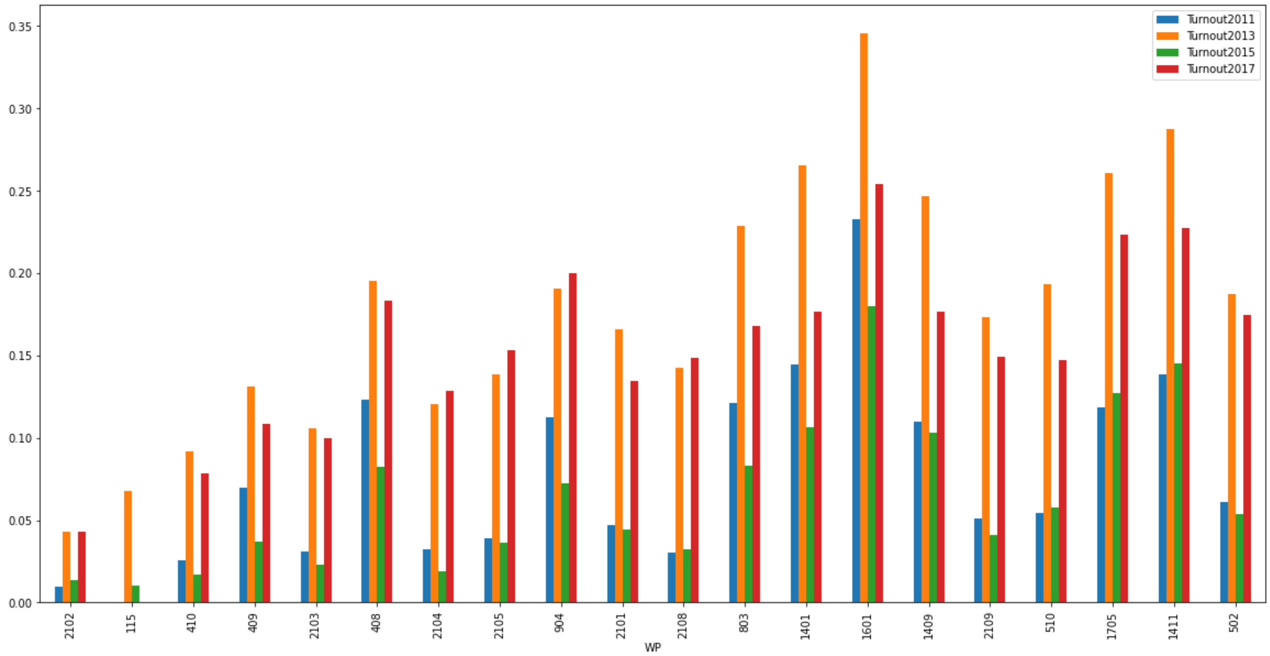
	WP	Turnout2011	Turnout2013	Turnout2015	Turnout2017	Diff11_13	Diff13_15	Diff15_17
226	2102	0.009475	0.042741	0.013972	0.042870	0.033267	0.028769	0.028898
14	115	0.000000	0.067568	0.010526	0.000000	0.067568	0.057041	0.010526
39	410	0.025397	0.091667	0.017196	0.078105	0.066270	0.074471	0.060909
38	409	0.069479	0.131491	0.037133	0.108520	0.062012	0.094358	0.071387
227	2103	0.030808	0.105505	0.022889	0.099558	0.074697	0.082616	0.076669
...	...	...	...	...	...	...	...	...
12	113	0.170962	0.514525	0.095393	0.332463	0.343563	0.419132	0.237071
10	111	0.202640	0.569517	0.157428	0.397193	0.366877	0.412089	0.239765
217	2013	0.269737	0.648734	0.197959	0.388199	0.378997	0.450775	0.190240
13	114	0.139509	0.523711	0.083164	0.343750	0.384202	0.440547	0.260586
11	112	0.214850	0.600766	0.147806	0.397070	0.385916	0.452960	0.249264

253 rows × 10 columns

In [20]:

```
#visualizing these top 20
top_change[:20].plot(x="WP", y=["Turnout2011", "Turnout2013", "Turnout2015", "Tu
```

Out[20]: <AxesSubplot:xlabel='WP'>



Preliminary Analysis of these Top 20 Precints

In [21]:

```
top_change[:20]
```

Out[21]:

	WP	Turnout2011	Turnout2013	Turnout2015	Turnout2017	Diff11_13	Diff13_15	Diff15_17
226	2102	0.009475	0.042741	0.013972	0.042870	0.033267	0.028769	0.028898
14	115	0.000000	0.067568	0.010526	0.000000	0.067568	0.057041	0.010526
39	410	0.025397	0.091667	0.017196	0.078105	0.066270	0.074471	0.060909
38	409	0.069479	0.131491	0.037133	0.108520	0.062012	0.094358	0.071387
227	2103	0.030808	0.105505	0.022889	0.099558	0.074697	0.082616	0.076669
37	408	0.123411	0.195553	0.082353	0.183020	0.072142	0.113200	0.100667
228	2104	0.032673	0.120424	0.019289	0.128352	0.087751	0.101135	0.109063
229	2105	0.039186	0.138661	0.036533	0.153312	0.099475	0.102128	0.116779
80	904	0.112206	0.190892	0.072570	0.199717	0.078687	0.118323	0.127148
225	2101	0.047313	0.166098	0.044686	0.134724	0.118785	0.121412	0.090038
232	2108	0.030266	0.142435	0.032219	0.148380	0.112169	0.110216	0.116161
72	803	0.121113	0.228754	0.082880	0.168182	0.107641	0.145873	0.085301
120	1401	0.144279	0.265350	0.106521	0.176494	0.121071	0.158829	0.069973
143	1601	0.232443	0.345803	0.180157	0.253940	0.113360	0.165646	0.073784
128	1409	0.110035	0.246812	0.102837	0.176929	0.136776	0.143975	0.074092

	WP	Turnout2011	Turnout2013	Turnout2015	Turnout2017	Diff11_13	Diff13_15	Diff15_17
233	2109	0.050741	0.172973	0.040759	0.148984	0.122232	0.132214	0.108225
49	510	0.054684	0.193119	0.057794	0.146924	0.138436	0.135325	0.089130
159	1705	0.118207	0.260870	0.127252	0.223489	0.142663	0.133617	0.096237
130	1411	0.138695	0.287629	0.145545	0.227116	0.148934	0.142084	0.081571
41	502	0.061207	0.187452	0.053989	0.174451	0.126245	0.133463	0.120462

In [32]:

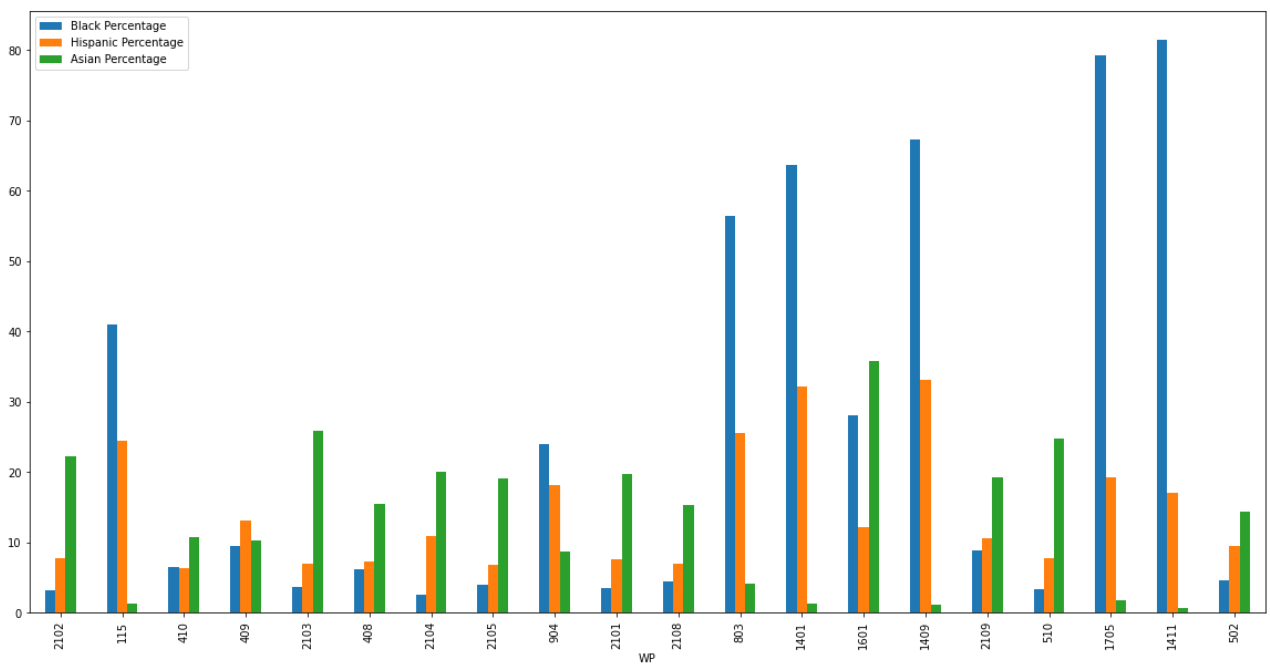
```
top20 = cc2011.iloc[[226, 14, 39, 38, 227, 37, 228, 229, 80, 225, 232, 72, 120,
```

Breakdown by racial demographics:

In [35]:

```
top20.plot(x="WP", y=["Black Percentage", "Hispanic Percentage", "Asian Percenta
```

Out[35]: <AxesSubplot:xlabel='WP'>



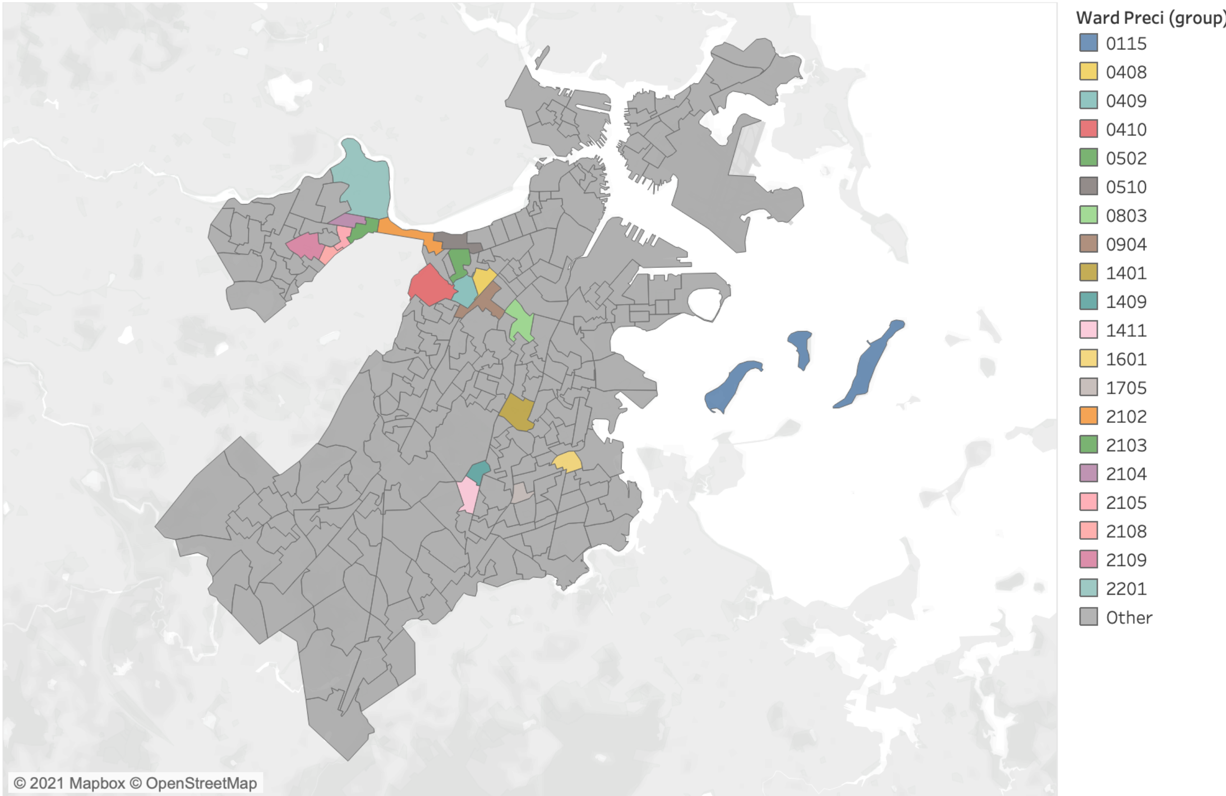
Showcasing these precincts geographically:

In [37]:

```
from IPython.display import Image
Image("Top20ChangeCC.png")
```

Out[37]:

Top 20 Precincts with Greatest Change across CC Election



Map based on Longitude (generated) and Latitude (generated). Color shows details about Ward Preci (group). Details are shown for Ward Preci.