0 Preamble

0.0 Initialize Environment

Start Warning

Run the following only if you need to **initialize** source data for the entire project environment.

In [ ]:
```
%run grabSource.py
```

Run the following only if you need to **overwrite** source data for the entire project environment.

In [ ]:
```
%run grabSource.py overwrite
```

End Warning

0.1 Global Packages

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
from scipy import stats
```

0.2 Local Packages

In [2]:
```
from ingestRaw import *
from transformClean import *
from segmentData import congressPresidentParty
from segmentFunctions import *
```

0.3 Import Data

In [3]:
```
congressVotes_raw = ingestCongressVote()
```

1 Data Mining

1.1 Verify Data Types

In [4]:
```
congressVotes_raw.dtypes
```

Out[4]:
```
congress                          Int64
chamber                          object
rollnumber                        Int64
date                      datetime64[ns]
session                           Int64
clerk_rollnumber                  Int64
yea_count                         Int64
nay_count                         Int64
nominate_mid_1                  float64
nominate_mid_2                  float64
nominate_spread_1               float64
nominate_spread_2               float64
nominate_log_likelihood         float64
bill_number                      object
vote_result                      object
vote_desc                        object
vote_question                    object
dtl_desc                         object
dtype: object
```

1.2 Initial Distributions

In [5]:
```
congressVotes_raw.describe(include= 'all').transpose()
```

Out[5]:

	count	unique	top	freq	mean	min
congress	111753.0	<NA>	<NA>	<NA>	73.920467	1.0
chamber	111753	2	House	59125	NaN	NaN
rollnumber	111753.0	<NA>	<NA>	<NA>	368.390665	1.0
date	111753	NaN	NaN	NaN	1936-01-13 13:05:30.997825792	1789-05-16 00:00:00
session	33447.0	<NA>	<NA>	<NA>	1.437139	1.0
clerk_rollnumber	33447.0	<NA>	<NA>	<NA>	279.685622	1.0
yea_count	111753.0	<NA>	<NA>	<NA>	123.063506	0.0
nay_count	111753.0	<NA>	<NA>	<NA>	75.268816	0.0
nominate_mid_1	111753.0	NaN	NaN	NaN	0.003677	-1.0
nominate_mid_2	111753.0	NaN	NaN	NaN	0.011355	-1.0
nominate_spread_1	111753.0	NaN	NaN	NaN	0.009661	-2.523
nominate_spread_2	111753.0	NaN	NaN	NaN	-0.00862	-8.037
nominate_log_likelihood	111753.0	NaN	NaN	NaN	-45.255432	-303.886
bill_number	87840	15840	HR1	633	NaN	NaN
vote_result	33447	64	Passed	12024	NaN	NaN
vote_desc	24949	17578	In the nature of a substitute.	256	NaN	NaN
vote_question	33439	721	On Agreeing to the Amendment	7201	NaN	NaN
dtl_desc	87943	85745	TO ADJOURN.	559	NaN	NaN

1.3 Preliminary Filtering

Voting outcomes are freeform text entry and have changed over time from the reporting source. Results for this analysis reduce the `Vote Result` to clear Pass/Fail markers. These markers are only used in recent years, beginning at Congress Number 101 (1989). This reduction produces sufficient results to conduct reasonable analysis without any claims to the utility of older data.

In [6]:
```
resultInclude = ['Passed', 'Failed']
congressVotes_clean = congressVotes_raw.query(
    f"vote_result in {resultInclude}"
)
congressVotes_clean = congressVotes_clean.drop(
    columns= [
        'session',
        'rollnumber',
        'clerk_rollnumber',
        'vote_question',
        'vote_desc',
        'dtl_desc'
    ]
)
```

1.4 Appending Segments

In [7]:
```
congressVotes_clean = pd.merge(
    congressVotes_clean,
    pd.DataFrame(congressPresidentParty, columns= ['congress', 'president_party']),
    how= 'left',
    on= 'congress'
)
```

1.5 Final Distributions

In [8]:
```
congressVotes_clean.describe(include= 'all').transpose()
```

Out[8]:

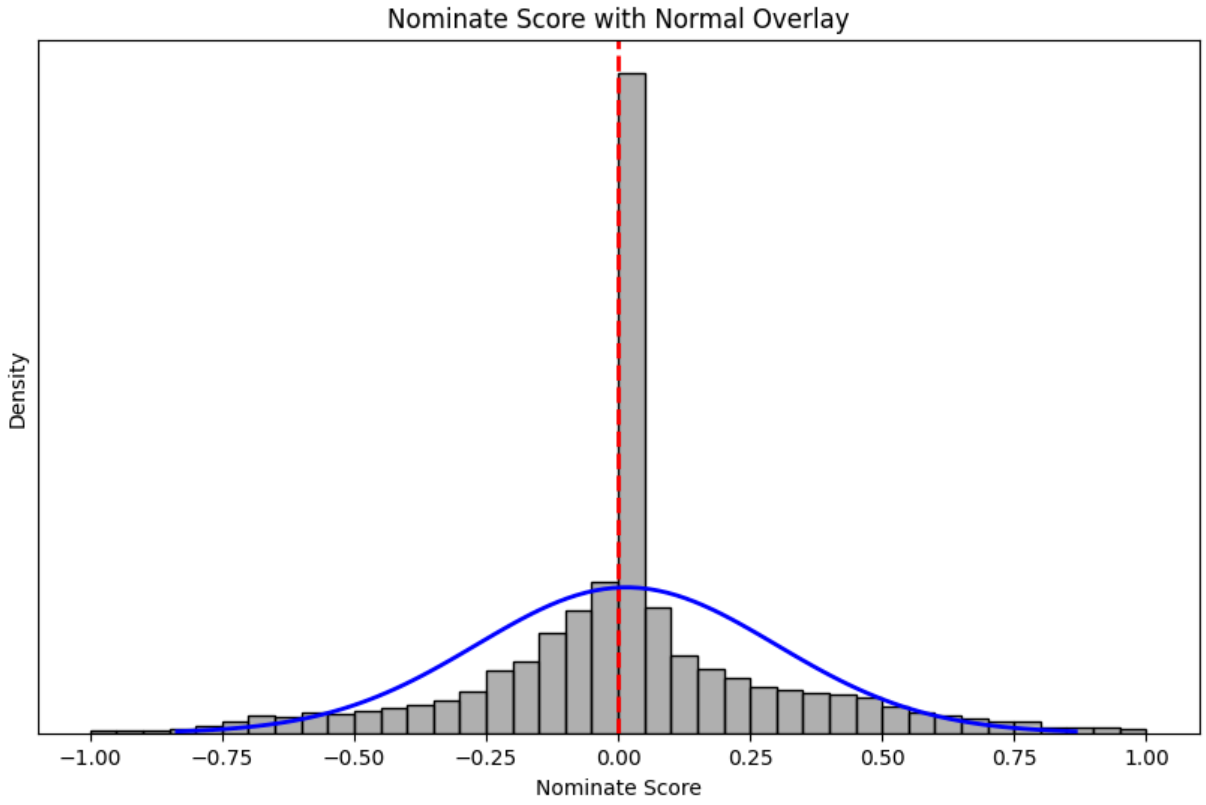
	count	unique	top	freq	mean	min
congress	18849.0	<NA>	<NA>	<NA>	109.857181	101.0
chamber	18849	1	House	18849	NaN	NaN
date	18849	NaN	NaN	NaN	2007-08-28 17:15:15.040585472	1990-01-24 00:00:00
yea_count	18849.0	<NA>	<NA>	<NA>	260.250464	0.0
nay_count	18849.0	<NA>	<NA>	<NA>	153.634782	0.0
nominate_mid_1	18849.0	NaN	NaN	NaN	0.015747	-1.0
nominate_mid_2	18849.0	NaN	NaN	NaN	0.051274	-1.0
nominate_spread_1	18849.0	NaN	NaN	NaN	0.008296	-1.85
nominate_spread_2	18849.0	NaN	NaN	NaN	-0.001108	-6.046
nominate_log_likelihood	18849.0	NaN	NaN	NaN	-57.191051	-303.886
bill_number	17838	5717	HR1	133	NaN	NaN
vote_result	18849	2	Passed	12024	NaN	NaN
president_party	18849	2	Democrat	10993	NaN	NaN

2 Distribution Analysis

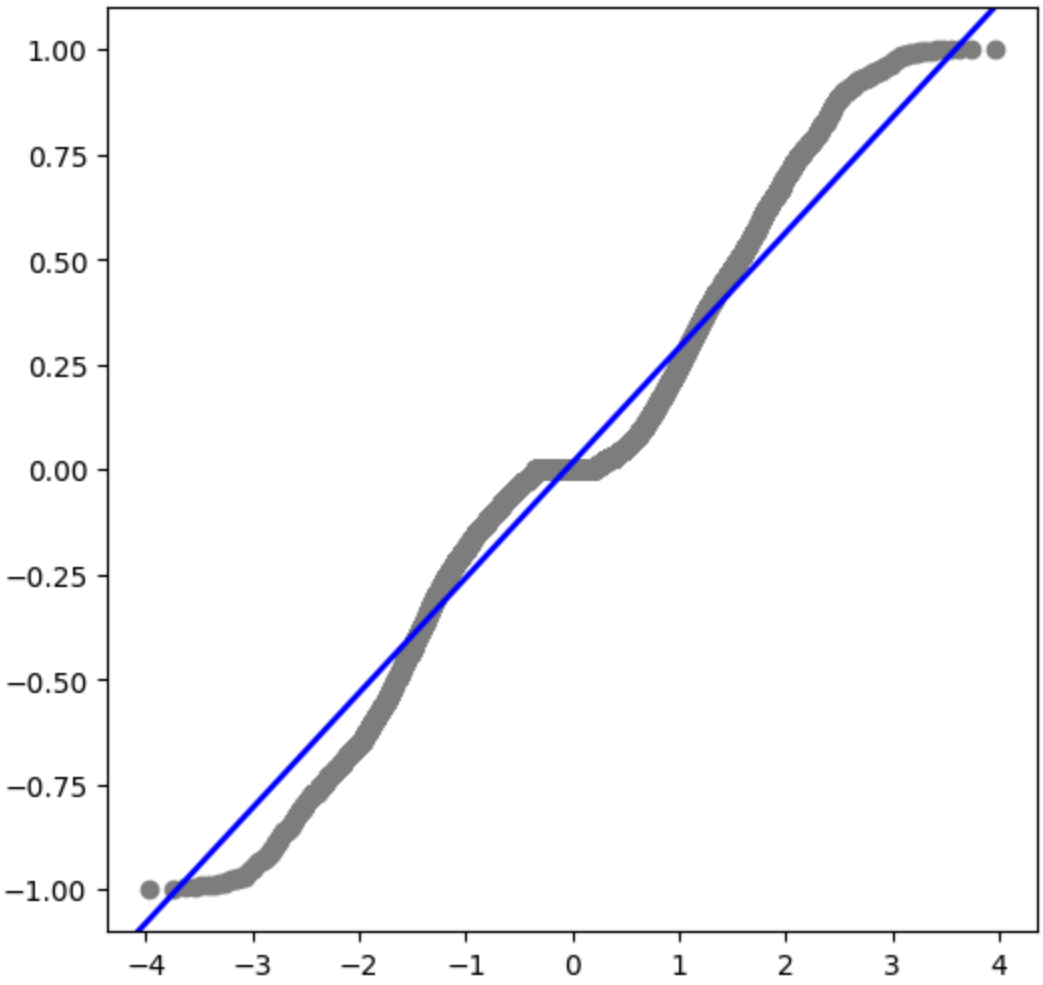
2.1 Testing Normality

In [9]:

```
sample = congressVotes_clean['nominate_mid_1'].tolist()
s_mean = np.mean(sample)
s_mid = np.median(sample)
s_dev = np.std(sample)
plt.figure(figsize=(10, 6))
sns.histplot(sample, bins=40, kde=False, color='gray', alpha=0.6, stat= 'density')
plt.axvline(s_mid, color='red', linestyle='dashed', linewidth= 2)
x = np.linspace(s_mean - 3*s_dev, s_mean + 3*s_dev, 100)
pdf = stats.norm.pdf(x, s_mean, s_dev)
plt.plot(x, pdf, color='blue', linestyle='solid', linewidth= 2)
plt.yticks([])
plt.xlabel('Nominate Score')
plt.title('Nominate Score with Normal Overlay')
plt.show()
```



In [10]:
```
res = stats.probplot(congressVotes_clean['nominate_mid_1'], dist= 'norm')
q_theoretic, q_sample = res[0][0], res[0][1]
slope, intercept = res[1][0], res[1][1]
se = stats.sem(q_theoretic)
upper_CI = q_theoretic*slope + intercept + 1.96 * se
lower_CI = q_theoretic*slope + intercept - 1.96 * se
fig, ax = plt.subplots(figsize=(6, 6))
ax.plot(q_theoretic, q_sample, 'o', color='gray')
ax.axline(
    (0, intercept),
    slope= slope,
    color= 'blue',
    lw= 2
)
plt.show()
```



Visual inspection of the data shows a modicum normality in its distribution. However, given the large size of the population data, the *visually* minor deviations from normality break the necessary assumptions of the population being a normal distribution for the purposes of statistical metrics.

Additionally, because of the dataset size, formal statistical tests of significance with normality are an inappropriate and inviable measure of determinance because the observation count overpowers the testing power of the statistic. Bootstrapping the test mitigates some of this issue even though the results (below) futher confirm the non-normality of the population.

In [11]:
```
testsNormality = pd.DataFrame()
for i in range(100):
    stats.shapiro(congressVotes_clean['nominate_mid_1'].sample(1000))
    _tests = congressVotes_clean.groupby('congress').apply(lambda x: stats.shapiro(
    testsNormality[i] = _tests.apply(lambda x: round(x[1], 4))
x = len(testsNormality[(testsNormality > 0).any(axis= 1)])
f"Number of non-zero probability results in 100 bootstrapped tests: {x}"
```

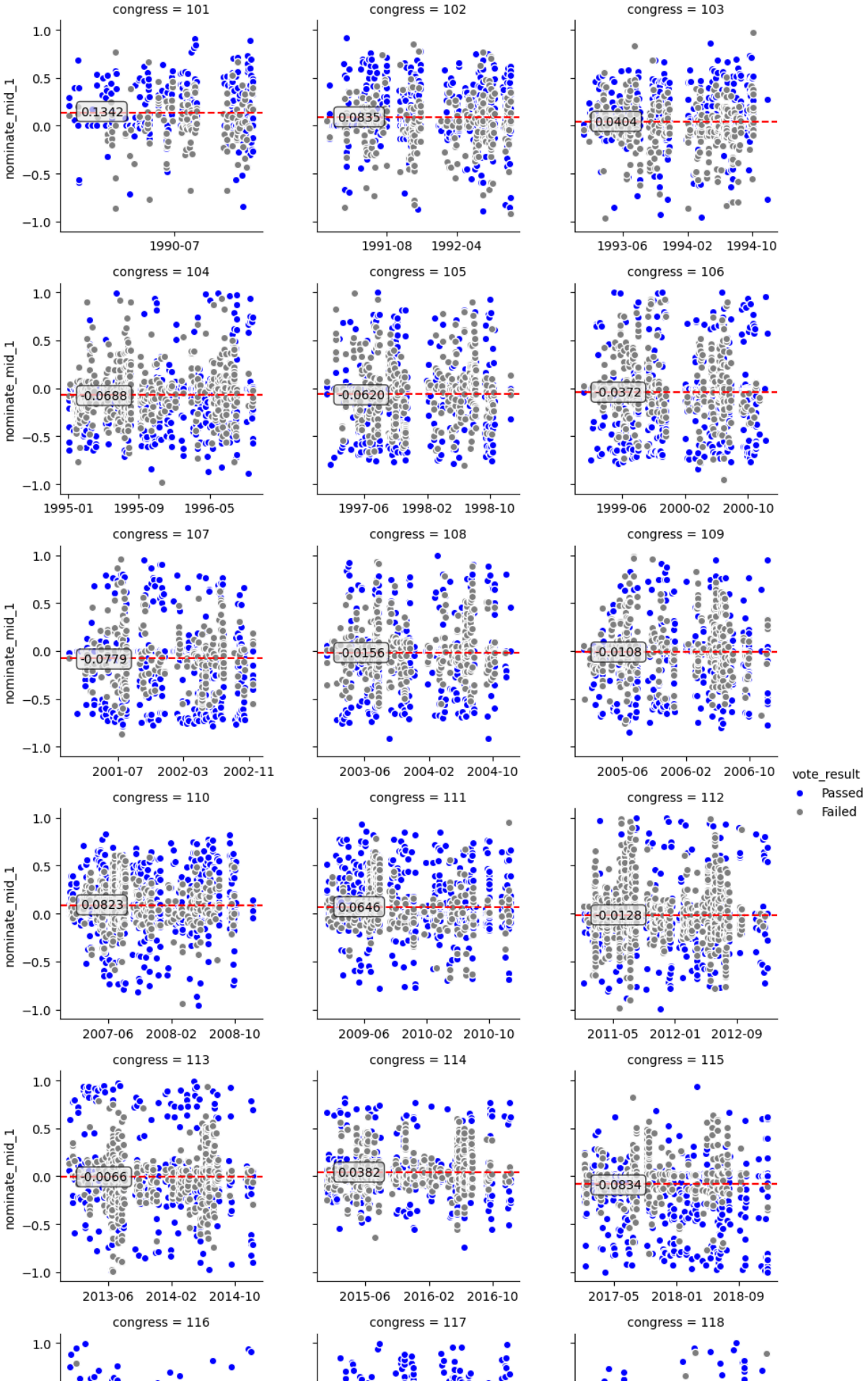
Out[11]:
```
'Number of non-zero probability results in 100 bootstrapped tests: 0'
```

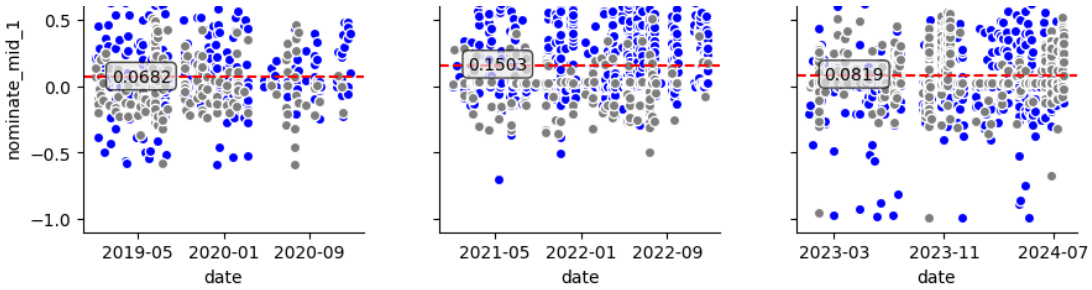
2.2 Grouping Considerations

An assumptive expectation of this report is the Congressional Sessions are functionally different from each other or progressively deviate over time and Presidential terms. Changes in Congress would manifest on the nominate spectrum (Liberal v Conservative) through changes in measures of central tendency and variability.

2.2(a) Moments of Mean

In [12]:
```
g = sns.FacetGrid(
    congressVotes_clean,
    sharex= False,
    col_wrap= 3,
    col= 'congress',
    hue= 'vote_result',
    palette= {
        'Passed': 'blue',
        'Failed': 'gray'
    }
)
g.map(plt.scatter, 'date', 'nominate_mid_1', edgecolor= "w").add_legend()
for ax, (group_name, group_data) in zip(g.axes.flat, congressVotes_clean.groupby('c
    mean_nominate = group_data['nominate_mid_1'].mean()
    ax.axhline(mean_nominate, color= 'red', linestyle= 'dashed')
    ax.text(
        x= .1, y= (mean_nominate + 1)/2,
        s= f"{mean_nominate:.4f}",
        transform= ax.transAxes,
        va= 'center',
        bbox= dict(boxstyle= "round", fc= "#ededed", alpha= .7)
    )
for ax in g.axes.flat:
    ax.xaxis.set_major_locator(mdates.MonthLocator(interval= 8))
plt.show()
```


congress = 101
congress = 102
congress = 103
congress = 104
congress = 105
congress = 106
congress = 107
congress = 108
congress = 109
congress = 110
congress = 111
congress = 112
congress = 113
congress = 114
congress = 115
congress = 116
congress = 117
congress = 118
nominate_mid_1
0.1342
0.0835
0.0404
-0.0688
-0.0620
-0.0372
-0.0779
-0.0156
-0.0108
0.0823
0.0646
-0.0128
-0.0066
0.0382
-0.0834
vote_result
Passed
Failed



In [13]:
```
subsetPass = congressVotes_clean[congressVotes_clean['vote_result'] == 'Passed']
df1 = testMannWhitney(
    congressVotes_clean,
    'congress',
    'nominate_mid_1',
    alternative= 'two-sided'
).rename(columns= {"P-Value": "P-Value FULL"}).drop(columns= "U-Statistic").set_ind
df2 = testMannWhitney(
    congressVotes_clean[congressVotes_clean['vote_result'] == 'Passed'],
    'congress',
    'nominate_mid_1',
    alternative= 'two-sided'
).rename(columns= {"P-Value": "P-Value PASS"}).drop(columns= "U-Statistic").set_ind

statsMannWhitney = df1.join(
    df2, how= 'outer')
statsMannWhitney[(statsMannWhitney > .05).any(axis= 1)].round(4)
```

Out[13]:

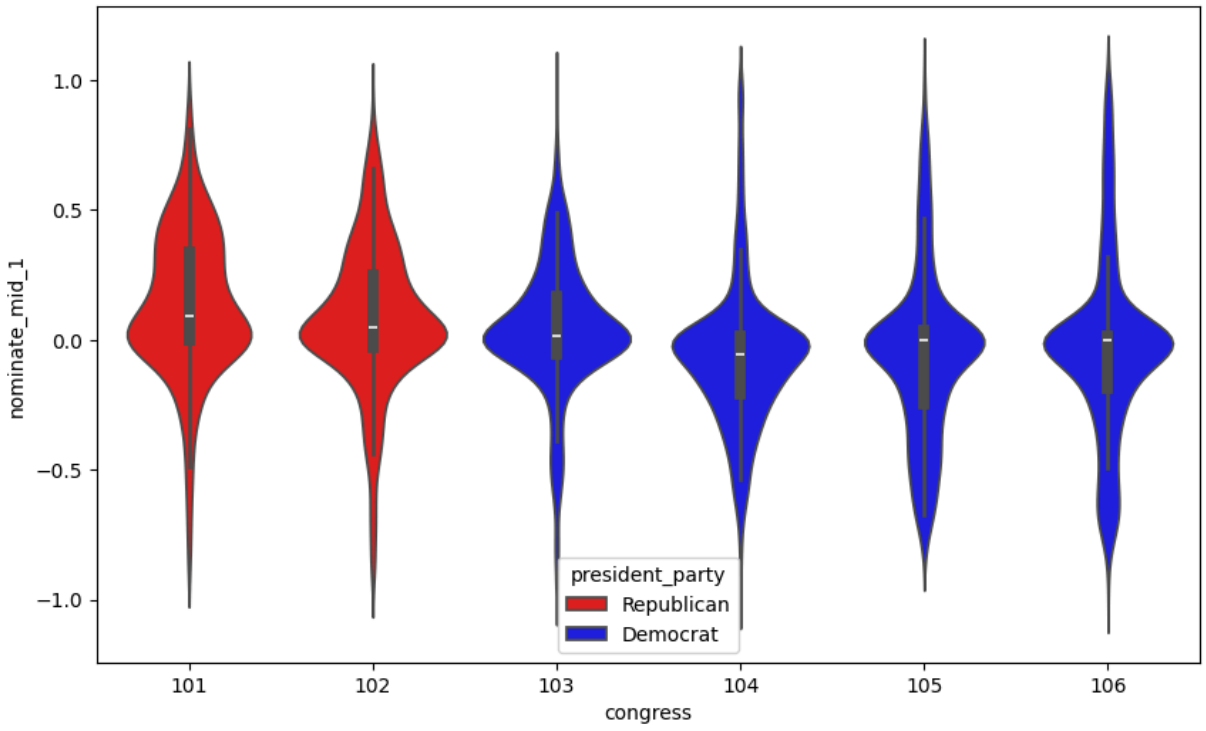
congress_1	congress_2	P-Value FULL	P-Value PASS
101	**117**	0.8038	0.4316
102	**110**	0.2069	0.0000
	118	0.8440	0.0000
103	**111**	0.9986	0.0000
	116	0.1003	0.6549
104	**105**	0.1095	0.1688
	106	0.0006	0.1163
	107	0.2226	0.0276
	112	0.0000	0.7804
105	**106**	0.2078	0.9568
	107	0.4377	0.5012
	112	0.0099	0.1641
	115	0.0859	0.1064
106	**107**	0.0668	0.4338
	112	0.4338	0.0716
	115	0.3801	0.0264
107	**115**	0.0016	0.1271
108	**109**	0.3072	0.6265
	113	0.9787	0.3892
109	**113**	0.4101	0.4938
110	**116**	0.2706	0.0007
	118	0.0639	0.0920
111	**118**	0.0000	0.2023
112	**113**	0.1133	0.0000
	115	0.3117	0.0010
113	**114**	0.0000	0.1271
116	**118**	0.0516	0.0000

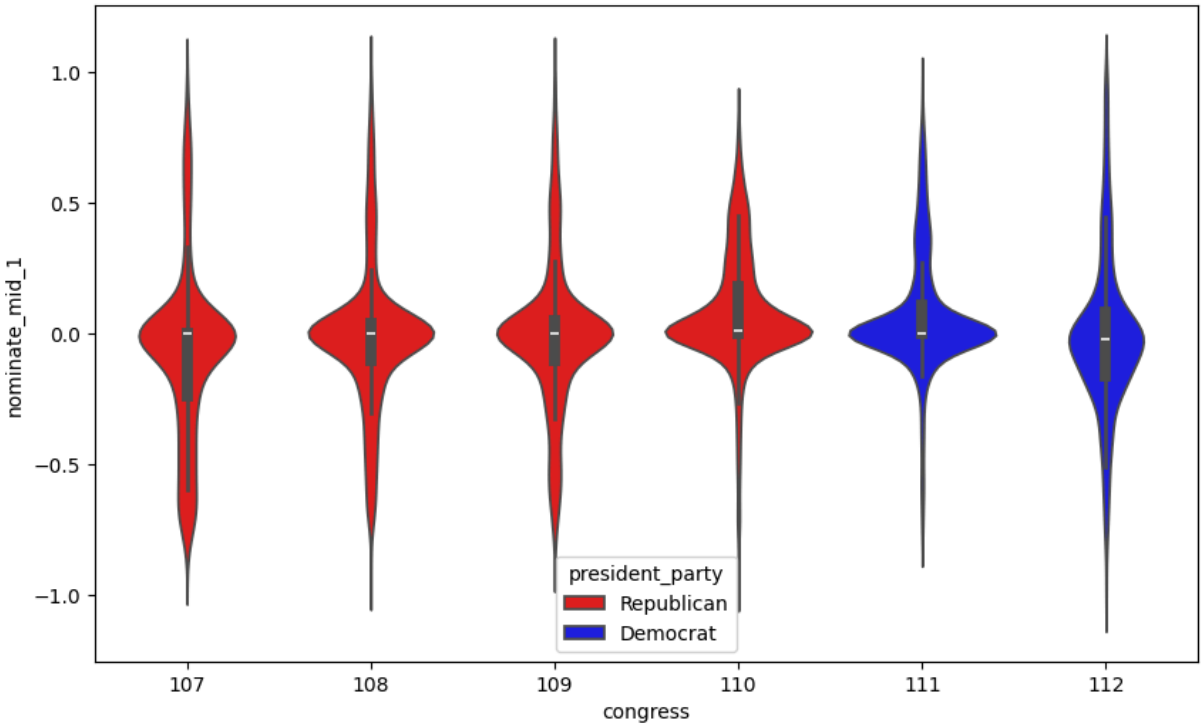
The nominate mean scores for each Congress are very near zero and have minimal fluctuation, suggesting the distributions (about the mean) of the entire dataset do not vary

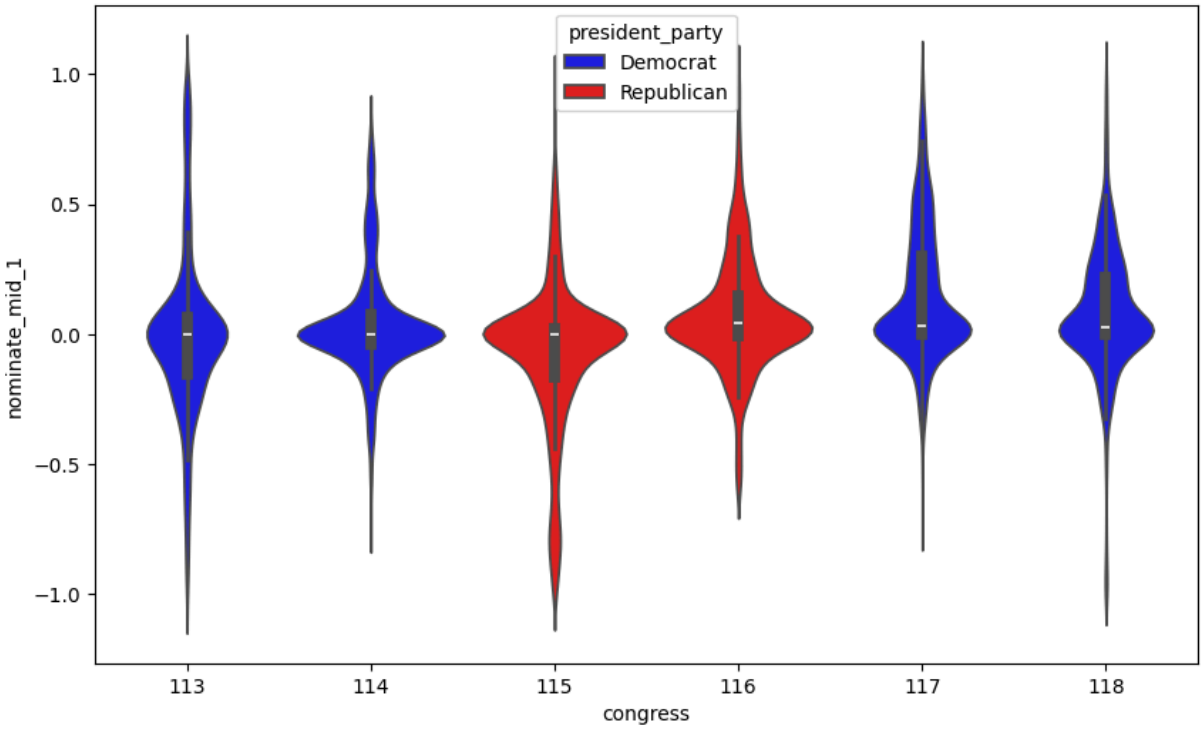
much at the subsetting of each Congressional Session. While there were instances of every Congress failing to reject the Null of the MannWhitney test, it's notable the pattern is inconsistent when accounting for expected similarities of adjacent Sessions or similar party compositions.

2.2(b) Moments of Variance

In [14]:
```
plt.figure(figsize=(10, 6))
sns.violinplot(
    congressVotes_clean[congressVotes_clean['congress'].between(101, 106)],
    x= 'congress', y= 'nominate_mid_1', hue= 'president_party',
    palette={'Republican': 'red', 'Democrat': 'blue'})
plt.show()
plt.figure(figsize=(10, 6))
sns.violinplot(
    congressVotes_clean[congressVotes_clean['congress'].between(107, 112)],
    x= 'congress', y= 'nominate_mid_1', hue= 'president_party',
    palette={'Republican': 'red', 'Democrat': 'blue'})
plt.show()
plt.figure(figsize=(10, 6))
sns.violinplot(
    congressVotes_clean[congressVotes_clean['congress'].between(113, 118)],
    x= 'congress', y= 'nominate_mid_1', hue= 'president_party',
    palette={'Republican': 'red', 'Democrat': 'blue'})
plt.show()
```







Unlike the evaluation of the mean with each Congress, the variance of nominate scores in each Congress are not alike and have a large deviation from their adjacent session numbers; identifying the Presidential party by color futher suggests there is no similarity by the controlling political direction. This shows that (adjacent) time and Presidential term have no influence over maintaining a homogeneous Congressional body.

In [15]:
```
statsFlignerKilleen = testFlignerKilleen(
    congressVotes_clean,
    'congress',
```

```
    'nominate_mid_1'
).set_index(['congress_1', 'congress_2'])
statsFlignerKilleen[statsFlignerKilleen['P-Value'] > 0.05]
```

Out[15]:

		F-Statistic	P-Value
congress_1	**congress_2**		
101	**102**	2.951981	0.085772
	105	0.000253	0.987301
	106	1.207169	0.271894
	112	3.446848	0.063373
102	**104**	2.077593	0.149476
	105	1.429748	0.231806
	106	0.008113	0.928230
	107	2.095153	0.147767
	112	0.043467	0.834848
	113	1.135791	0.286543
103	**107**	0.537586	0.463435
	113	3.365391	0.066580
	117	0.013017	0.909164
	118	2.234465	0.134963
104	**106**	0.834449	0.360989
	107	0.405101	0.524467
	112	1.932455	0.164490
	113	0.000572	0.980925
105	**106**	3.273554	0.070405
	112	0.705325	0.401000
106	**107**	1.944735	0.163155
	112	0.464275	0.495633
	113	0.051944	0.819715
	117	3.483006	0.062002
107	**113**	2.323881	0.127402
	115	2.622761	0.105341
	117	0.098244	0.753948
	118	1.481963	0.223468
108	**109**	1.777416	0.182467

		F-Statistic	P-Value
congress_1	**congress_2**		
	110	1.156731	0.282144
	115	2.894726	0.088870
	116	1.203002	0.272723
109	**110**	0.997220	0.317984
	115	0.005993	0.938294
	116	0.244353	0.621080
	118	1.428072	0.232079
110	**115**	0.716279	0.397367
	116	0.550549	0.458094
	118	3.673943	0.055269
112	**113**	1.694659	0.192988
113	**117**	3.342221	0.067523
115	**116**	0.266338	0.605799
116	**118**	1.906856	0.167313
117	**118**	2.060120	0.151198

The only notable similarity between each Congress appears to be when the incumbent party retains it's control with subsequent Congressional Sessions; this is the only component to align with the initial assumptions made by this report.