What characteristics correlate with Voting Rate

A friend of mine running for the local council has procured the voter registration data for the area and shared it with me. Here is an initial investigation of voter characteristics and how they correlate with Voting Rate.

Prior to this analysis the data has been cleaned, all personally identifying data removed and some additional featured created by manipulating the available information.

In [1]:
```
# imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from modules.lv_utils import load_households
from modules.lv_utils import load_voters
```

In [2]:
```
# load the data
households = load_households('data_clean/20180628_fullset_households_district3.csv')
voters = load_voters('data_clean/20180628_fullset_voters_district3.csv')
elections = pd.read_csv('data_clean/20180621_election_data.csv')

# set parameters for vote rate columns for the individual and household levels
cols_vr = ['E34_nVotesPct', 'E56_nVotesPct', 'E78_nVotesPct']
cols_vr_hh = ['E34_nVotesPctInHH','E56_nVotesPctInHH','E78_nVotesPctInHH']
```

Defining various methods and functions used to present the data.

In [3]:
```
def vote_data_plus_fields(fields, inc_HHvd=False, inc_Vid=True):
    """
    Returns the voter rate columns with requested fields in a dataframe.
    All fields have missing values replaced with NaNs.
    """
    # including the vote rate household fields if requested
    vr = cols_vr + cols_vr_hh if inc_HHvd else cols_vr

    # including the 'Vid' field if requested
    cols = vr + ['Vid'] + fields if inc_Vid else vr + fields

    # creating the df requested
    df = voters.loc[:, cols]

    # converting cleaned not known data ie 'UNK' to NaNs
    for f in fields:
        # replacing 'UNK' with Nan to indicate no data if fields has any 'UNK'
        if 'UNK' in df.loc[:,f].value_counts().index.values.astype(str):
            df.loc[:,f].replace('UNK', np.NaN, inplace=True)

    # replacing '-1' indicating no data for vote with NaN
    for c in df[vr]:
        df[c].replace(-1, np.NaN, inplace=True)

    return df
```

In [4]:
```
def vote_rate_as_pct(df, prefix):
    """
    Calculates the vote rates as a % of the voters in that group.
    ie what % of E34 voters are a 0 vote rate, and what % have 0.5 and what have a 1.
    prints out the number of voters in each group - ie the sample size.
    """
    out = []
    print('{} has:'.format(prefix))
    for i,f in enumerate(['E34_nVotesPct','E56_nVotesPct','E78_nVotesPct']):
        fcount = df[f].count()
        out.append(df[[f,'Vid']].groupby(f).agg('count')/fcount)
        out[i] = out[i].reset_index().rename(columns={f:'VoteRate',
                                                      'Vid': prefix+'_'+f[:4]+'Votes'})
        out[i].VoteRate = round(out[i].VoteRate,2).astype('str')
        print('    n = {} for {} data'.format(fcount, f[:3]))

    return  pd.merge(
                pd.merge(out[0],out[1], on='VoteRate', how='outer'),
                    out[2], on='VoteRate', how='outer').set_index('VoteRate').sort_index()
```

In [5]:
```
def plot_groups(df, title):
    """
    Takes in a list of dataframes and plots a bar chart of the data against voterate
    Each df contains the data for each of the three main vote rates.
    One dataframe for each group you want to compare.
    """
    colors = [('lightblue','lightskyblue','deepskyblue'),
              ('palegreen','mediumseagreen','forestgreen'),
              ('navajowhite','orange','darkorange'),
              ('lightgrey','silver','darkgrey')]
    offsets = {2:[(-2,0,2),(-3,-1,1)],
               4:[(-6,-2,2),(-5,-1,3),(-4,0,4),(-3,1,5)]}
    ndfs = len(df)
    widths = {2:0.015,
              4:0.01}

    fig, ax = plt.subplots()

    for i, d in enumerate(df):
        w = widths[ndfs]
        shs = offsets[ndfs][i]
        cs = colors[i]
        for j, dd in enumerate([d[[c]].dropna() for c in d.columns]):
            sh = shs[j]*w
            ax.bar(dd.index.astype('float')+sh, dd.iloc[:,0],
                   w, alpha=0.7, align='edge', label=dd.columns[0], color=cs[j])

    plt.legend(bbox_to_anchor=(0.75,1))
    plt.ylabel('%of Voters in group')
    plt.xlabel('Vote Rate (1 is always vote, 0 is never votes)')
    plt.title(title)
    plt.show()
```

In [6]:
```
def vote_rate_diff_always_never_two_groups(df, prefix):
    """
    Takes in a list of two dataframes and presents the difference between them.
    """
    [df1,df2] = [d.loc[['0.0','1.0'],:] for d in df]
    df1.columns = [c.replace(prefix[0],'') for c in df1.columns]
    df2.columns = [c.replace(prefix[1],'') for c in df2.columns]
    return df1-df2
```

In [7]:
```
def plot_hist_vote_rate_vs_field(ax, df, voteRatef, field):
    """
    Spliting the provided data into sometimes, always and never voters and drawing
    a histogram of the three vote categories on the provided axis.
    """
    a, b = 0.3, 16
    df1 = pd.DataFrame(df[[voteRatef, field]]).rename(columns = {voteRatef:'VR'})
    always, sometimes, never = (df1.VR == 1), (df1.VR < 1) & (df1.VR > 0), (df1.VR == 0)

    ax.hist(df1.loc[sometimes, field], bins=b, alpha=a, label='SomeTimesVoters')
    ax.hist(df1.loc[always, field], bins=b, alpha=a, label='AlwaysVoters')
    ax.hist(df1.loc[never, field], bins=b, alpha=a, label='NeverVoters')

    ax.legend(loc='upper left')
    return ax
```

All Voters in our dataset

In [8]:
```
print('Our data covers one district, containing information about {} Voters and {} Households.'.format(
        voters.shape[0], households.shape[0]))
```

```
Our data covers one district, containing information about 13307 Voters and 6930 Households.
```

To illuminate voting behavior and allow future development of trainable models predicting vote rate, the vote rate was Calculated on a scale of 0-1 from the data available. 1 is 'always' voted, 0 is never voted, and numbers in between indicate likelihood to vote, higher is more likely.

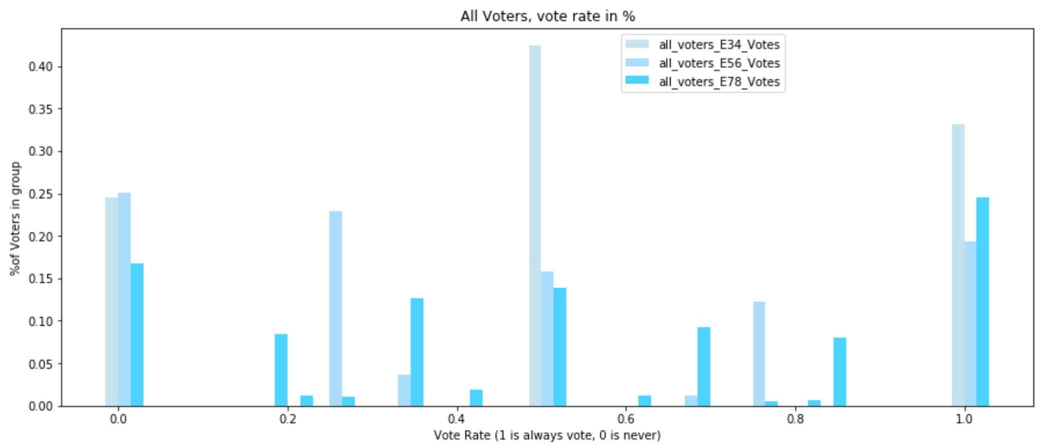
- E34 data is Vote Rate calculated from the 2012 Primary and General elections only (this was a presidential year).
- E56 data is Vote Rate calculated from the 2012 & 2014 Primary and General elections (so votes from both a presidential year and a congressional year).
- E78 data is Vote Rate calculated from the 2012, 2014 & 2016 Primary and General elections so data from voting habits of up to 6 elections.

Not all currently registered voters were also registered in this same district in 2012, and conversely we only have data from 2012 from voters who are still registered in this district. The data about 2012 voting habits has, as expected, therefore the smallest number of data points.

In [9]:
```
df = vote_data_plus_fields([])
df = vote_rate_as_pct(df, 'all_voters')
```

```
all_voters has:
    n = 9303 for E34 data
    n = 10043 for E56 data
    n = 12378 for E78 data
```

In [10]:
```
plt.rcParams["figure.figsize"] = (15,6)
fig, ax = plt.subplots()
cs = ('lightblue','lightskyblue','deepskyblue')
w = 0.015
shs = (-1,0,1)
for idx, dd in enumerate([df[[c]].dropna() for c in df.columns]):
    sh = shs[idx]*w
    #ax.bar(dd.index.astype('float')+sh, dd.iloc[:,0])
    ax.bar(dd.index.astype('float')+sh, dd.iloc[:,0],
           w, alpha=0.7, align='edge', label=dd.columns[0], color=cs[idx])

plt.legend(bbox_to_anchor=(0.75,1))
plt.ylabel('%of Voters in group')
plt.xlabel('Vote Rate (1 is always vote, 0 is never)')
plt.title('All Voters, vote rate in %')
plt.show()

df.transpose()
```



Out[10]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
all_voters_E34_Votes	0.245405	NaN	NaN	NaN	NaN	NaN	0.423734	NaN	NaN	NaN	NaN	NaN	0.330861
all_voters_E56_Votes	0.250921	NaN	NaN	0.228318	0.036443	NaN	0.157324	NaN	0.012048	0.122075	NaN	NaN	0.192871
all_voters_E78_Votes	0.167555	0.084182	0.011634	0.010503	0.126434	0.018258	0.139279	0.011391	0.092422	0.005170	0.007109	0.080304	0.245759

As expected we get a more spread distribution the more years of election data we use when calculating vote rate.

You can also see that almost half the voters we have 2012 information for sometimes voted and sometimes didn't - likely they voted in the general but not the primary (open primary system in CA started in 2010).

You can also see in the E56 data which has one presidential year and one congressional year of vote behavior included a greater % of voters have lower probabilities of voting. 25% of voters are never voters and 22% have only voted once in the 4 elections in this calculation.

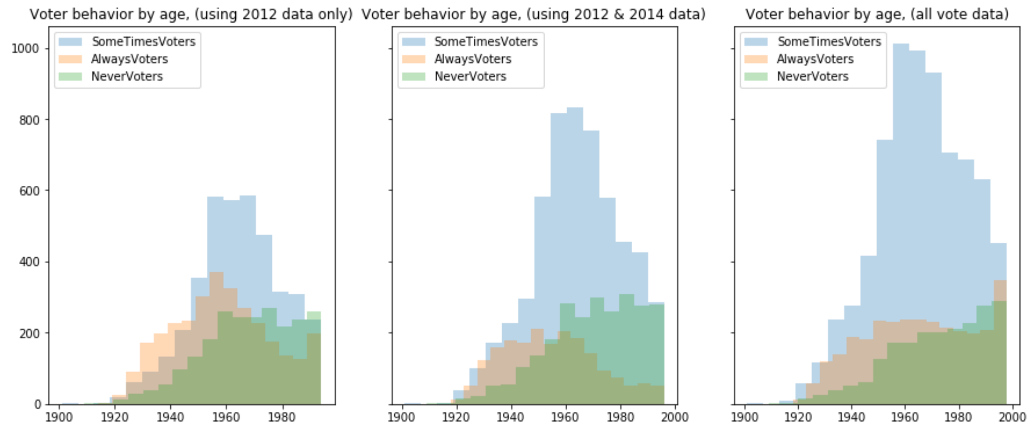
Fewer people vote in congressional cycles.

How does Age affect vote rate (aka BirthYear)

In [11]:
```
df = vote_data_plus_fields(['BirthYear'])
old = df.BirthYear < 1901
young = df.BirthYear > 1995
#print(df[old | young].BirthYear.value_counts().sort_index())
print('There are {} people over 100 (inc {} people entering 1900 which is likely bad data)'.format(
df[df.BirthYear < 1918].BirthYear.count(),df[df.BirthYear == 1900].BirthYear.count()))
print('As you would expect some people ({}) register as they turn 18'.format(
df[df.BirthYear == 2000].BirthYear.count()))

print('\nThe {} voters who have 1900 entered for their BirthYears have been removed'.format(
df[old].BirthYear.count()))
# cutting out the outliers
df = df[~old]
```

```
There are 12 people over 100 (inc 7 people entering 1900 which is likely bad data)
As you would expect some people (32) register as they turn 18

The 7 voters who have 1900 entered for their BirthYears have been removed
```

In [12]:
```
fig, (ax1,ax2,ax3) = plt.subplots(1,3, sharey=True)
ax1 = plot_hist_vote_rate_vs_field(ax1, df, 'E34_nVotesPct', 'BirthYear')
ax1.set_title('Voter behavior by age, (using 2012 data only)')

ax2 = plot_hist_vote_rate_vs_field(ax2, df, 'E56_nVotesPct', 'BirthYear')
ax2.set_title('Voter behavior by age, (using 2012 & 2014 data)')

ax3 = plot_hist_vote_rate_vs_field(ax3, df, 'E78_nVotesPct', 'BirthYear')
ax3.set_title('Voter behavior by age, (all vote data)')

plt.show()
```



You can see in these histograms that the Always Voters skew older (having birth years to the left of the graphs) and the Never Voters skew younger with birth years to the right of the graphs.

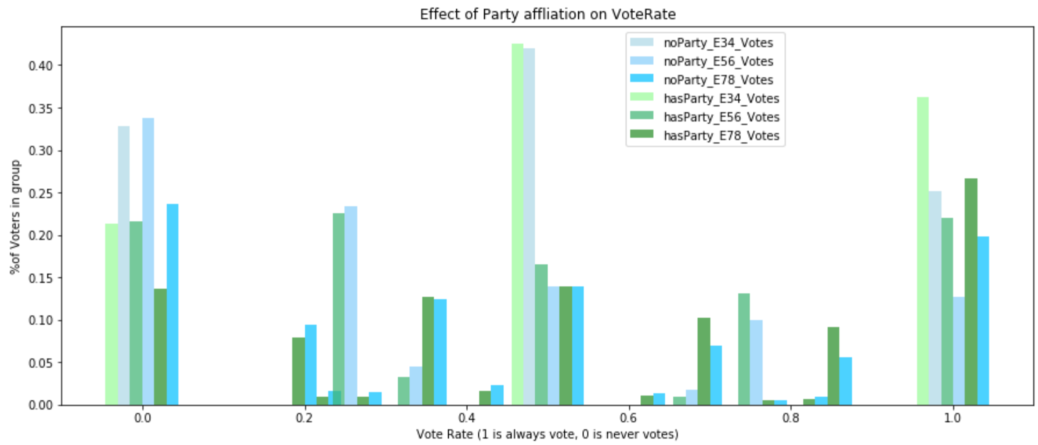
You can also see that the young were particularly likely to drop out of the Always vote group during the congressional cycle in 2014.

Grouping the voters by hasParty

In [12]:
```
df = vote_data_plus_fields(['HasParty'])
dfm = []
pre = ['noParty', 'hasParty']
for key, grp in df.groupby(['HasParty']):
    dfm.append(vote_rate_as_pct(grp, pre[key]))
```

```
noParty has:
    n = 2605 for E34 data
    n = 2903 for E56 data
    n = 3794 for E78 data
hasParty has:
    n = 6698 for E34 data
    n = 7140 for E56 data
    n = 8584 for E78 data
```

In [13]:
```
plot_groups(dfm, 'Effect of Party affliation on VoteRate')
pd.concat([d for d in dfm], axis=1).transpose()
```



Out[13]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
noParty_E34_Votes	0.328215	NaN	NaN	NaN	NaN	NaN	0.420345	NaN	NaN	NaN	NaN	NaN	0.251440
noParty_E56_Votes	0.337926	NaN	NaN	0.233896	0.044437	NaN	0.139166	NaN	0.017568	0.099552	NaN	NaN	0.127454
noParty_E78_Votes	0.236690	0.094623	0.016342	0.014760	0.124671	0.022404	0.139167	0.013706	0.069584	0.005799	0.008698	0.055614	0.197944
hasParty_E34_Votes	0.213198	NaN	NaN	NaN	NaN	NaN	0.425052	NaN	NaN	NaN	NaN	NaN	0.361750
hasParty_E56_Votes	0.215546	NaN	NaN	0.226050	0.033193	NaN	0.164706	NaN	0.009804	0.131232	NaN	NaN	0.219468
hasParty_E78_Votes	0.136999	0.079567	0.009553	0.008621	0.127213	0.016426	0.139329	0.010368	0.102516	0.004893	0.006407	0.091216	0.266892

In [14]:
```
print('% noParty voters - % hasParty voters')
print('    for the never vote and always vote voters ')
vote_rate_diff_always_never_two_groups(dfm, pre)
```

```
% noParty voters - % hasParty voters
    for the never vote and always vote voters
```

Out[14]:

	_E34_Votes	_E56_Votes	_E78_Votes
VoteRate			
0.0	0.115017	0.122380	0.099690
1.0	-0.110310	-0.092013	-0.068948

You can see that blue (noParty) bars are taller on the left of the graph and green (hasParty) bars are taller on the right of the graph. Looking at bar sizes you can see that a voter with an a party affiliation is ~10% more likely to be an always voter group and 10% less likely to be a never voter.

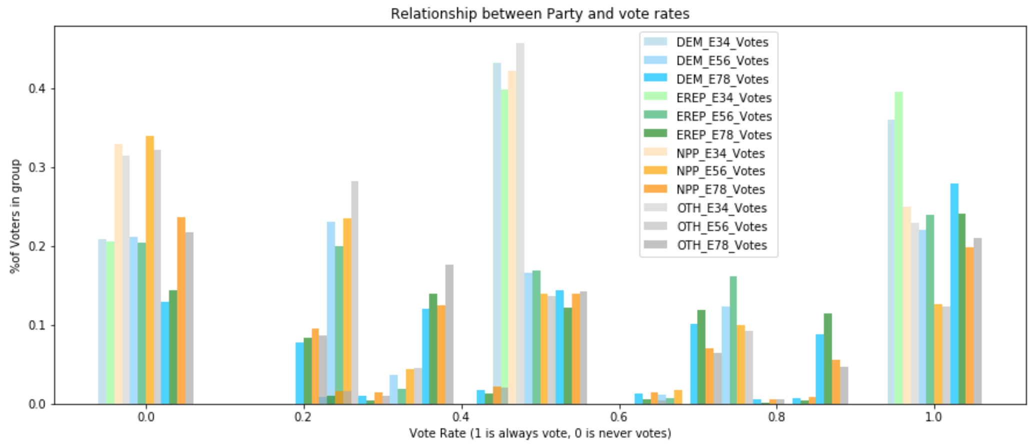
Note for the hasParty flag people with 'UNK' party affiliation were marked 'False' or noParty.

Grouping by PartyMain

In [15]:
```
df = vote_data_plus_fields(['PartyMain'])
# renaming to enable alpha sort to put DEM and REP next to each other
df['PartyMain'].replace('REP', 'EREP', inplace=True)

dfm = []
for key, grp in df.groupby(['PartyMain']):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
DEM has:
    n = 4702 for E34 data
    n = 5057 for E56 data
    n = 6232 for E78 data
EREP has:
    n = 1650 for E34 data
    n = 1703 for E56 data
    n = 1865 for E78 data
NPP has:
    n = 2597 for E34 data
    n = 2894 for E56 data
    n = 3781 for E78 data
OTH has:
    n = 346 for E34 data
    n = 380 for E56 data
    n = 487 for E78 data
```

In [18]:
```
title = 'Relationship between Party and vote rates'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[['0.0','1.0'],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[18]:

	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
DEM_E34_Votes	0.208209	NaN	NaN	NaN	NaN	NaN	0.431944	NaN	NaN	NaN	NaN	NaN	0.359847
DEM_E56_Votes	0.211390	NaN	NaN	0.230769	0.037176	NaN	0.165513	NaN	0.011272	0.123789	NaN	NaN	0.220091
DEM_E78_Votes	0.128851	0.077985	0.008825	0.009949	0.119865	0.017169	0.144416	0.012356	0.100610	0.005777	0.007542	0.087612	0.279044
EREP_E34_Votes	0.206061	NaN	NaN	NaN	NaN	NaN	0.398788	NaN	NaN	NaN	NaN	NaN	0.395152
EREP_E56_Votes	0.204345	NaN	NaN	0.199648	0.018790	NaN	0.168526	NaN	0.007634	0.162067	NaN	NaN	0.238990
EREP_E78_Votes	0.143164	0.083110	0.010188	0.003753	0.138874	0.012869	0.121716	0.005362	0.119035	0.001609	0.004290	0.114745	0.241287
NPP_E34_Votes	0.328841	NaN	NaN	NaN	NaN	NaN	0.421255	NaN	NaN	NaN	NaN	NaN	0.249904
NPP_E56_Votes	0.338977	NaN	NaN	0.234278	0.043884	NaN	0.139254	NaN	0.017277	0.099516	NaN	NaN	0.126814
NPP_E78_Votes	0.236974	0.094684	0.016398	0.014811	0.125099	0.021952	0.139381	0.013753	0.069558	0.005554	0.008463	0.055805	0.197567
OTH_E34_Votes	0.315029	NaN	NaN	NaN	NaN	NaN	0.456647	NaN	NaN	NaN	NaN	NaN	0.228324
OTH_E56_Votes	0.321053	NaN	NaN	0.281579	0.044737	NaN	0.136842	NaN	NaN	0.092105	NaN	NaN	0.123684
OTH_E78_Votes	0.217659	0.086242	0.016427	0.010267	0.176591	0.020534	0.141684	0.004107	0.063655	0.006160	NaN	0.047228	0.209446

You can see clearly that having a party preference of one of the two main parties increases your likelihood of always voting (blue and green taller on right of graph, gray taller on left of graph). The affect is much less marked if you are a member of one of the minor parties, and having No Party Preference means you are most likely to be a never voter, 23% to 33% of NPP voters never vote.

You can also see that across the board there is less voting in the congressional years.

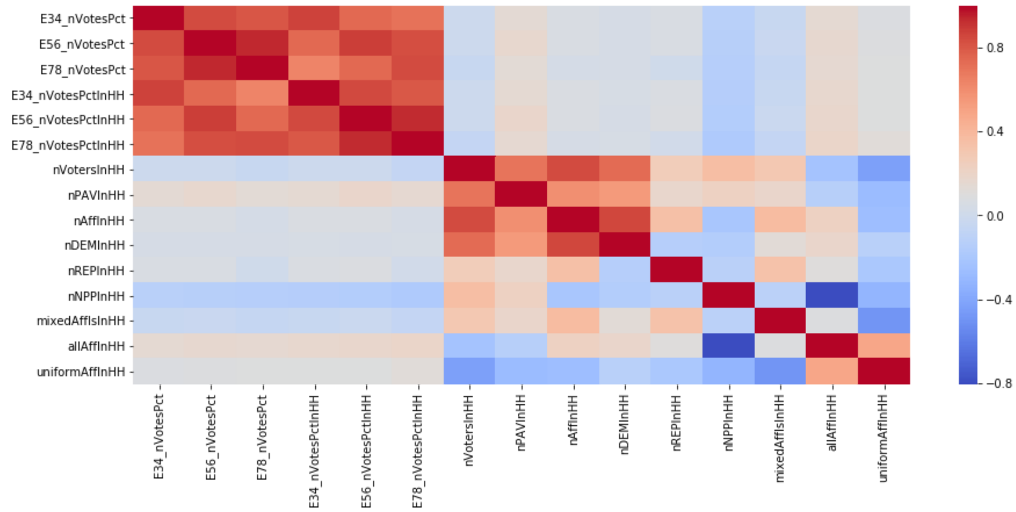
It is also interesting to notice that a larger share of Rep's were always voters in the 2012 cycle while a larger share of Dem's were in the 2016 cycle this is probably the 'energized' effect of having a sitting president you want to unseat.

Note the NPP number are slightly different to the earlier HasParty analysis as this data removed the 27 'UNK' rather than assumed they were NPP's.

Cohort vote rate calculations would help bring out the effects of the election cycle in the data.

Full Correlation Matrix of Household characteristics

```
In [18]: df = vote_data_plus_fields(['nVotersInHH','nPAVInHH','nAffInHH','nDEMInHH','nREPInHH','nNPPInHH',
                                   'mostAfflsInHH','mixedAfflsInHH','allAffInHH','uniformAffInHH'],
                                   inc_HHvd = True, inc_Vid=False)
         # plot the heatmap
         sns.heatmap(df.corr(),
                 xticklabels=df.corr().columns,
                 yticklabels=df.corr().columns, cmap='coolwarm')
         plt.show()
```



You can see a slight positive correlation with voting for Permanent Absentee Voters, and living in a HH where everyone is affiliated with a party. You can see slight negative correlations with the number of people with No Party Preference, and living in mixed Affiliated households. There is also a slight negative correlation with the over all number of voters in your household.

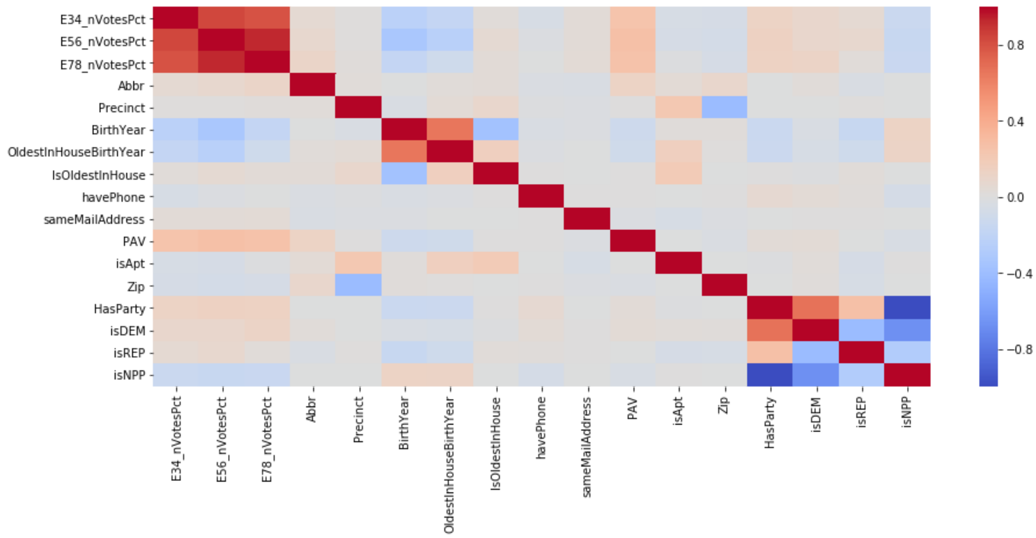
```
In [19]: df.corr()
```

Out[19]:

	E34_nVotesPct	E56_nVotesPct	E78_nVotesPct	E34_nVotesPctInHH	E56_nVotesPctInHH	E78_nVotesPctInHH	nVotersInHH	nPAVInHH	nAffInHH
E34_nVotesPct	1.000000	0.843985	0.804988	0.871113	0.741618	0.707058	-0.008784	0.144556	0.066193
E56_nVotesPct	0.843985	1.000000	0.937424	0.742861	0.887154	0.833945	-0.013671	0.175707	0.063595
E78_nVotesPct	0.804988	0.937424	1.000000	0.636085	0.741332	0.843682	-0.037855	0.138059	0.040014
E34_nVotesPctInHH	0.871113	0.742861	0.636085	1.000000	0.849744	0.801297	-0.011247	0.153921	0.074126
E56_nVotesPctInHH	0.741618	0.887154	0.741332	0.849744	1.000000	0.929707	-0.012976	0.184958	0.072659
E78_nVotesPctInHH	0.707058	0.833945	0.843682	0.801297	0.929707	1.000000	-0.056542	0.156195	0.043213
nVotersInHH	-0.008784	-0.013671	-0.037855	-0.011247	-0.012976	-0.056542	1.000000	0.698352	0.838194
nPAVInHH	0.144556	0.175707	0.138059	0.153921	0.184958	0.156195	0.698352	1.000000	0.598405
nAffInHH	0.066193	0.063595	0.040014	0.074126	0.072659	0.043213	0.838194	0.598405	1.000000
nDEMInHH	0.047330	0.043754	0.048880	0.051936	0.047870	0.050556	0.733060	0.542334	0.855793
nREPInHH	0.064150	0.067610	0.010542	0.076342	0.082730	0.019693	0.266372	0.177411	0.346693
nNPPInHH	-0.125954	-0.129836	-0.136764	-0.147917	-0.148792	-0.174242	0.359379	0.228002	-0.206162
mixedAfflsInHH	-0.035795	-0.031109	-0.050570	-0.041312	-0.028127	-0.060844	0.301742	0.187943	0.378784
allAffInHH	0.148626	0.162409	0.159256	0.171205	0.181913	0.193822	-0.228634	-0.133220	0.231490
uniformAffInHH	0.081222	0.085564	0.092429	0.097387	0.095743	0.120575	-0.431356	-0.277974	-0.264225

Full Correlation Matrix of Voter characteristics

In [20]:
```
df = vote_data_plus_fields(['Abbr','Precinct','BirthYear','OldestInHouseBirthYear','IsOldestInHouse',
                            'havePhone','sameMailAddress','PAV','isApt','Zip','HasParty',
                            'isDEM','isREP','isNPP'],
                            inc_HHvd = False, inc_Vid=False)
# converting PAV Y/N to True/False
df['PAV'] = df['PAV'].str.contains('Y')

# plot the heatmap
sns.heatmap(df.corr(),
        xticklabels=df.corr().columns,
        yticklabels=df.corr().columns, cmap='coolwarm')
plt.show()
```



Correlations can be see with Permanent Absentee Ballots, and age (negative birthYear), also with having a party affiliation and negatively with being a No Party Preference.

In [21]:
```
df.corr()
```

Out[21]:

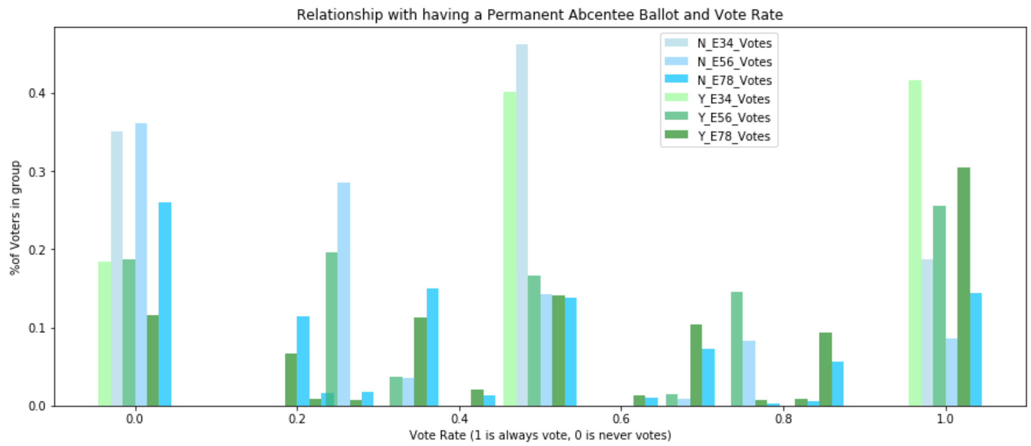
	E34_nVotesPct	E56_nVotesPct	E78_nVotesPct	Abbr	Precinct	BirthYear	OldestInHouseBirthYear	IsOldestInHouse	havePhone	sameM
E34_nVotesPct	1.000000	0.843985	0.804988	0.061162	0.010929	-0.228068	-0.175615	0.027021	-0.052187	0.03440
E56_nVotesPct	0.843985	1.000000	0.937424	0.081047	0.017089	-0.327751	-0.239807	0.057924	-0.016199	0.03833
E78_nVotesPct	0.804988	0.937424	1.000000	0.115448	0.021054	-0.170714	-0.100923	0.035346	-0.000426	0.04773
Abbr	0.061162	0.081047	0.115448	1.000000	0.030848	-0.000566	0.027531	0.037651	-0.028249	-0.0355
Precinct	0.010929	0.017089	0.021054	0.030848	1.000000	-0.030181	0.043500	0.088935	-0.010321	-0.0197
BirthYear	-0.228068	-0.327751	-0.170714	-0.000566	-0.030181	1.000000	0.660768	-0.365598	-0.036274	-0.0192
OldestInHouseBirthYear	-0.175615	-0.239807	-0.100923	0.027531	0.043500	0.660768	1.000000	0.163700	-0.015668	-0.0009
IsOldestInHouse	0.027021	0.057924	0.035346	0.037651	0.088935	-0.365598	0.163700	1.000000	0.009351	-0.0017
havePhone	-0.052187	-0.016199	-0.000426	-0.028249	-0.010321	-0.036274	-0.015668	0.009351	1.000000	0.00589
sameMailAddress	0.034408	0.038338	0.047737	-0.035555	-0.019754	-0.019242	-0.000947	-0.001746	0.005897	1.00000
PAV	0.253559	0.282039	0.264846	0.130060	0.006783	-0.114379	-0.097358	0.008503	0.004934	-0.0181
isApt	-0.046606	-0.058249	-0.012920	0.046193	0.227459	0.022714	0.165752	0.198518	0.002252	-0.0459
Zip	-0.055593	-0.070970	-0.054879	0.095783	-0.418098	0.024202	0.012582	-0.000394	0.007284	-0.0140
HasParty	0.134130	0.147570	0.139722	0.000406	-0.001257	-0.130194	-0.124105	0.005453	0.066768	0.00049
isDEM	0.088697	0.091782	0.124154	0.026616	-0.003371	-0.035936	-0.051586	-0.009127	0.041580	0.00405
isREP	0.063795	0.082165	0.028617	-0.033653	0.012132	-0.149292	-0.103749	0.031765	0.023659	0.00623
isNPP	-0.135627	-0.148844	-0.140250	-0.000326	0.000423	0.128147	0.122805	-0.004791	-0.063468	-0.0013

PAV voters

In [22]:
```
df = vote_data_plus_fields(['PAV'])
dfm = []
for key, grp in df.groupby(['PAV']):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
N has:
    n = 3439 for E34 data
    n = 3707 for E56 data
    n = 4479 for E78 data
Y has:
    n = 5864 for E34 data
    n = 6336 for E56 data
    n = 7899 for E78 data
```

In [23]:
```
title = 'Relationship with having a Permanent Abcentee Ballot and Vote Rate'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[[0,1],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[23]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
N_E34_Votes	0.351265	NaN	NaN	NaN	NaN	NaN	0.461762	NaN	NaN	NaN	NaN	NaN	0.186973
N_E56_Votes	0.360939	NaN	NaN	0.284866	0.035878	NaN	0.142163	NaN	0.008093	0.082547	NaN	NaN	0.085514
N_E78_Votes	0.259656	0.114758	0.016522	0.017191	0.150480	0.013619	0.137531	0.009600	0.073231	0.002456	0.005135	0.056486	0.143336
Y_E34_Votes	0.183322	NaN	NaN	NaN	NaN	NaN	0.401432	NaN	NaN	NaN	NaN	NaN	0.415246
Y_E56_Votes	0.186553	NaN	NaN	0.195234	0.036774	NaN	0.166193	NaN	0.014362	0.145202	NaN	NaN	0.255682
Y_E78_Votes	0.115331	0.066844	0.008862	0.006710	0.112799	0.020889	0.140271	0.012407	0.103304	0.006710	0.008229	0.093809	0.303836

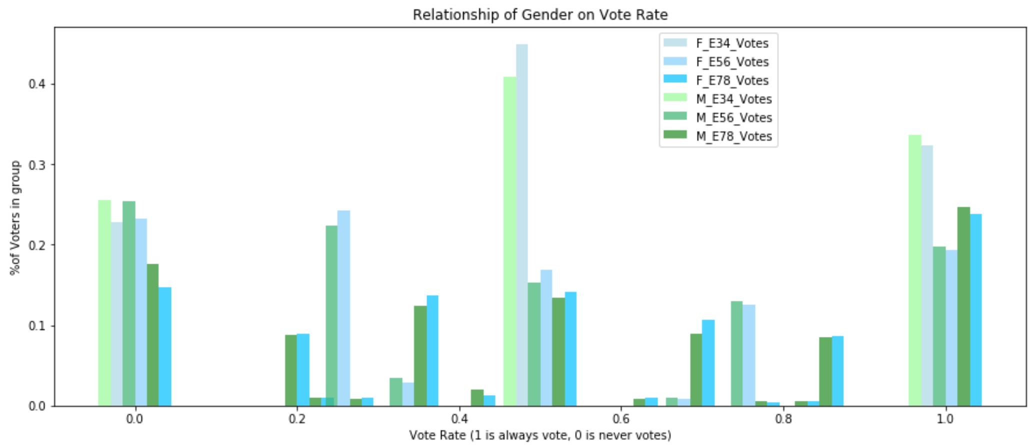
Having a permanent Absentee Ballot significantly increases the likelihood of your being in the always voter category.

Gender

In [24]:
```
df = vote_data_plus_fields(['Gender'])
df.Gender = df.Gender.cat.remove_categories('UNK')

#df.groupby(['Gender']).describe()

dfm = []
for key, grp in df.groupby(['Gender']):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
F has:
    n = 4455 for E34 data
    n = 4740 for E56 data
    n = 5651 for E78 data
M has:
    n = 4084 for E34 data
    n = 4355 for E56 data
    n = 5269 for E78 data
```

In [25]:
```
title = 'Relationship of Gender on Vote Rate'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[[0,1],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[25]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
F_E34_Votes	0.227834	NaN	NaN	NaN	NaN	NaN	0.448485	NaN	NaN	NaN	NaN	NaN	0.323681
F_E56_Votes	0.232068	NaN	NaN	0.242194	0.028903	NaN	0.168987	NaN	0.009072	0.125316	NaN	NaN	0.193460
F_E78_Votes	0.146346	0.089011	0.010441	0.010087	0.137321	0.012918	0.141037	0.010264	0.106707	0.004601	0.006017	0.086710	0.238542
M_E34_Votes	0.255632	NaN	NaN	NaN	NaN	NaN	0.408668	NaN	NaN	NaN	NaN	NaN	0.335700
M_E56_Votes	0.253731	NaN	NaN	0.223881	0.034214	NaN	0.152468	NaN	0.009185	0.129047	NaN	NaN	0.197474
M_E78_Votes	0.175555	0.087493	0.010249	0.008920	0.124502	0.019548	0.133422	0.008541	0.088821	0.004935	0.005694	0.085215	0.247106

Interestingly Females are less likely to be in the Always voter and less likely to be in the Never vote group than males by just a couple of percentage points!

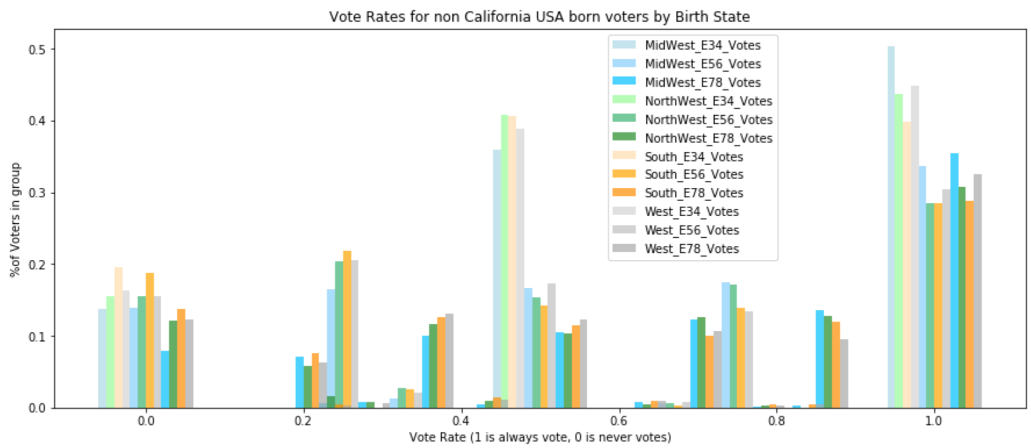
BirthState Region

Excluding Californians

In [26]:
```
df = vote_data_plus_fields(['BirthPlaceState','BirthPlaceStateRegion'])

# Removing Voters born in California
df.loc[df.BirthPlaceState == 'California', 'BirthPlaceStateRegion'] = np.NaN
df = df.drop('BirthPlaceState', axis=1)
#df.BirthPlaceStateRegion.value_counts()

dfm = []
#df.groupby(['BirthPlaceStateRegion']).describe()
for key, grp in df.groupby('BirthPlaceStateRegion'):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
MidWest has:
    n = 503 for E34 data
    n = 527 for E56 data
    n = 584 for E78 data
NorthWest has:
    n = 360 for E34 data
    n = 373 for E56 data
    n = 429 for E78 data
South has:
    n = 367 for E34 data
    n = 380 for E56 data
    n = 420 for E78 data
West has:
    n = 368 for E34 data
    n = 381 for E56 data
    n = 434 for E78 data
```

In [27]:
```python
title = 'Vote Rates for non California USA born voters by Birth State'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[[0,1],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[27]:

	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
MidWest_E34_Votes	0.137177	NaN	NaN	NaN	NaN	NaN	0.359841	NaN	NaN	NaN	NaN	NaN	0.502982
MidWest_E56_Votes	0.138520	NaN	NaN	0.165085	0.013283	NaN	0.166983	NaN	0.005693	0.174573	NaN	NaN	0.335863
MidWest_E78_Votes	0.078767	0.070205	0.006849	0.008562	0.099315	0.005137	0.104452	0.008562	0.123288	0.001712	0.003425	0.135274	0.354452
NorthWest_E34_Votes	0.155556	NaN	NaN	NaN	NaN	NaN	0.408333	NaN	NaN	NaN	NaN	NaN	0.436111
NorthWest_E56_Votes	0.155496	NaN	NaN	0.203753	0.026810	NaN	0.152815	NaN	0.005362	0.171582	NaN	NaN	0.284182
NorthWest_E78_Votes	0.121212	0.058275	0.016317	0.006993	0.116550	0.009324	0.102564	0.004662	0.125874	0.002331	NaN	0.128205	0.307692
South_E34_Votes	0.196185	NaN	NaN	NaN	NaN	NaN	0.405995	NaN	NaN	NaN	NaN	NaN	0.397820
South_E56_Votes	0.186842	NaN	NaN	0.218421	0.026316	NaN	0.142105	NaN	0.002632	0.139474	NaN	NaN	0.284211
South_E78_Votes	0.138095	0.076190	0.004762	NaN	0.126190	0.014286	0.114286	0.009524	0.100000	0.004762	0.004762	0.119048	0.288095
West_E34_Votes	0.163043	NaN	NaN	NaN	NaN	NaN	0.388587	NaN	NaN	NaN	NaN	NaN	0.448370
West_E56_Votes	0.154856	NaN	NaN	0.204724	0.020997	NaN	0.173228	NaN	0.007874	0.133858	NaN	NaN	0.304462
West_E78_Votes	0.122120	0.062212	0.002304	0.006912	0.131336	0.011521	0.122120	0.009217	0.105991	0.002304	0.004608	0.094470	0.324885

There doesn't seem to be a strong pattern for voting behavior for people born out of CA, grouped by birth region. West and MidWest born voters are slightly more likely to end up in the always vote category than Southern born voters.

BirthCountry

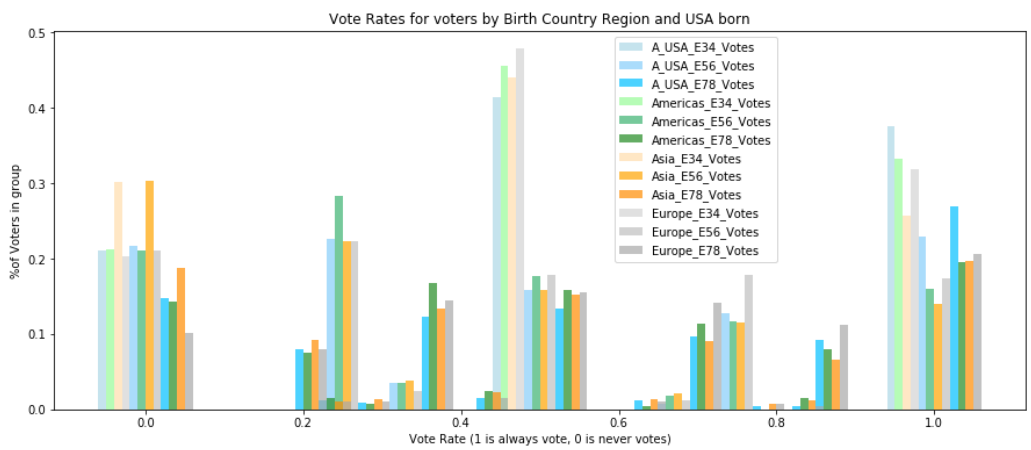
In [28]:
```python
df = vote_data_plus_fields(['BirthPlaceCountry','BirthPlaceCountryRegion'])

print(df.BirthPlaceCountryRegion.value_counts())

# removing Oceania and Africa as sample size is too small
df['BirthPlaceCountryRegion'].replace('Africa', np.NaN, inplace=True)
df['BirthPlaceCountryRegion'].replace('Oceania', np.NaN, inplace=True)
df = df.drop('BirthPlaceCountry', axis=1)

df['BirthPlaceCountryRegion'].replace('USA', 'A_USA', inplace=True)
```

```
USA         7074
Asia        3915
Americas     551
Europe       291
Africa        88
Oceania       59
Name: BirthPlaceCountryRegion, dtype: int64
```

In [29]:
```
dfm = []
df.groupby(['BirthPlaceCountryRegion']).describe()
for key, grp in df.groupby(['BirthPlaceCountryRegion']):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
A_USA has:
    n = 5302 for E34 data
    n = 5627 for E56 data
    n = 6741 for E78 data
Americas has:
    n = 428 for E34 data
    n = 452 for E56 data
    n = 529 for E78 data
Asia has:
    n = 2634 for E34 data
    n = 2935 for E56 data
    n = 3615 for E78 data
Europe has:
    n = 232 for E34 data
    n = 247 for E56 data
    n = 276 for E78 data
```

In [30]:
```
title = 'Vote Rates for voters by Birth Country Region and USA born'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[[0,1],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[30]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
A_USA_E34_Votes	0.210864	NaN	NaN	NaN	NaN	NaN	0.413806	NaN	NaN	NaN	NaN	NaN	0.375330
A_USA_E56_Votes	0.216279	NaN	NaN	0.226586	0.035365	NaN	0.157811	NaN	0.007464	0.127955	NaN	NaN	0.228541
A_USA_E78_Votes	0.147308	0.080552	0.012016	0.008752	0.122682	0.015576	0.134253	0.012164	0.096128	0.004450	0.004450	0.092568	0.269100
Americas_E34_Votes	0.212617	NaN	NaN	NaN	NaN	NaN	0.455607	NaN	NaN	NaN	NaN	NaN	0.331776
Americas_E56_Votes	0.210177	NaN	NaN	0.283186	0.035398	NaN	0.176991	NaN	0.017699	0.117257	NaN	NaN	0.159292
Americas_E78_Votes	0.143667	0.075614	0.015123	0.007561	0.168242	0.024575	0.158790	0.003781	0.113422	NaN	0.015123	0.079395	0.194707
Asia_E34_Votes	0.302202	NaN	NaN	NaN	NaN	NaN	0.440395	NaN	NaN	NaN	NaN	NaN	0.257403
Asia_E56_Votes	0.302555	NaN	NaN	0.223169	0.038842	NaN	0.158773	NaN	0.020784	0.115503	NaN	NaN	0.140375
Asia_E78_Votes	0.186999	0.092669	0.010788	0.014108	0.133610	0.023237	0.151867	0.013278	0.090456	0.008022	0.011895	0.066390	0.196680
Europe_E34_Votes	0.202586	NaN	NaN	NaN	NaN	NaN	0.478448	NaN	NaN	NaN	NaN	NaN	0.318966
Europe_E56_Votes	0.210526	NaN	NaN	0.222672	0.024291	NaN	0.178138	NaN	0.012146	0.178138	NaN	NaN	0.174089
Europe_E78_Votes	0.101449	0.079710	0.010870	0.010870	0.144928	0.014493	0.155797	0.010870	0.141304	0.007246	0.003623	0.112319	0.206522

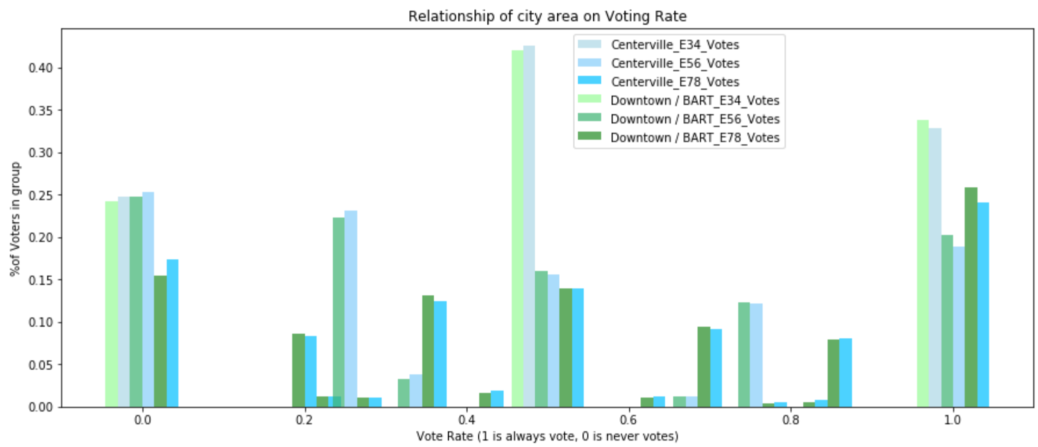
Voters born in Asia are more likely to end up in the never vote category. USA born voters are more likely to be in the Always vote category.

CityArea

```
In [31]: df = vote_data_plus_fields(['CityArea'])

print('Removing {} cityarea as our data only has {} voters in that area'.format(
df.CityArea.value_counts().index[-1],df.CityArea.value_counts()[-1]))

df['CityArea'].replace('Niles', np.NaN, inplace=True)

dfm = []
for key, grp in df.groupby(['CityArea']):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
Removing Niles cityarea as our data only has 3 voters in that area
Centerville has:
    n = 6508 for E34 data
    n = 7014 for E56 data
    n = 8612 for E78 data
Downtown / BART has:
    n = 2792 for E34 data
    n = 3026 for E56 data
    n = 3763 for E78 data
```

```
In [32]: title = 'Relationship of city area on Voting Rate'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[[0,1],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[32]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
Centerville_E34_Votes	0.247081	NaN	NaN	NaN	NaN	NaN	0.425169	NaN	NaN	NaN	NaN	NaN	0.327750
Centerville_E56_Votes	0.252638	NaN	NaN	0.230539	0.038067	NaN	0.156259	NaN	0.012261	0.121614	NaN	NaN	0.188623
Centerville_E78_Votes	0.173595	0.083720	0.011496	0.010451	0.124361	0.019392	0.139224	0.011844	0.091500	0.005574	0.008128	0.080469	0.240246
Downtown / BART_E34_Votes	0.241762	NaN	NaN	NaN	NaN	NaN	0.420129	NaN	NaN	NaN	NaN	NaN	0.338109
Downtown / BART_E56_Votes	0.247191	NaN	NaN	0.223397	0.032716	NaN	0.159617	NaN	0.011566	0.122935	NaN	NaN	0.202578
Downtown / BART_E78_Votes	0.153867	0.085304	0.011959	0.010630	0.131278	0.015679	0.139251	0.010364	0.094605	0.004252	0.004783	0.079724	0.258305

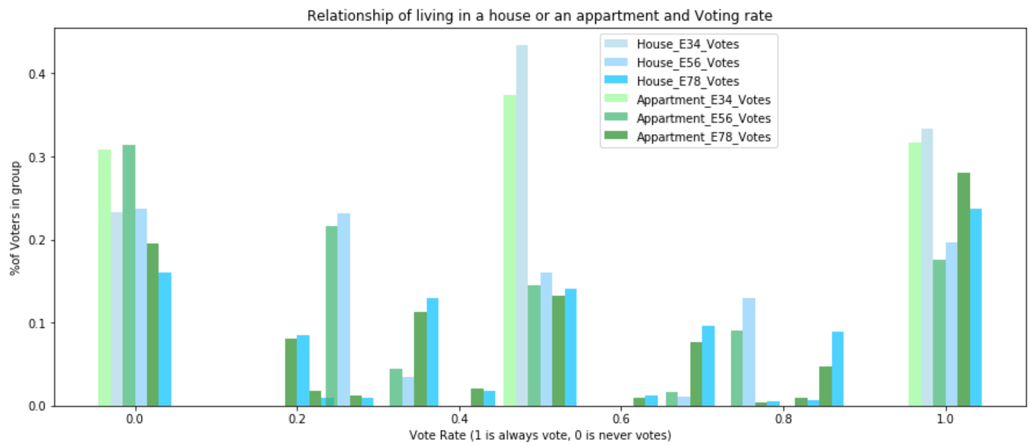
Voters in Centerville are a little more likely to end up in the never vote category and Downtown/BART voters in the always vote category. The effect is small and may not be real.

Living in an Apartment

```
In [33]: df = vote_data_plus_fields(['isApt'])
dfm = []
pre = ['House', 'Appartment']
for key, grp in df.groupby(['isApt']):
    dfm.append(vote_rate_as_pct(grp, pre[key]))
```

```
House has:
    n = 7727 for E34 data
    n = 8262 for E56 data
    n = 9906 for E78 data
Appartment has:
    n = 1576 for E34 data
    n = 1781 for E56 data
    n = 2472 for E78 data
```

In [34]:
```
title = 'Relationship of living in a house or an appartment and Voting rate'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[[0,1],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[34]:

VoteRate	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
House_E34_Votes	0.232432	NaN	NaN	NaN	NaN	NaN	0.433804	NaN	NaN	NaN	NaN	NaN	0.333765
House_E56_Votes	0.237352	NaN	NaN	0.231058	0.034858	NaN	0.160131	NaN	0.011014	0.129024	NaN	NaN	0.196563
House_E78_Votes	0.160711	0.084898	0.010095	0.009893	0.129820	0.017666	0.141026	0.012013	0.096305	0.005451	0.006360	0.088532	0.237230
Appartment_E34_Votes	0.309010	NaN	NaN	NaN	NaN	NaN	0.374365	NaN	NaN	NaN	NaN	NaN	0.316624
Appartment_E56_Votes	0.313869	NaN	NaN	0.215609	0.043796	NaN	0.144301	NaN	0.016844	0.089837	NaN	NaN	0.175744
Appartment_E78_Votes	0.194984	0.081311	0.017799	0.012945	0.112864	0.020631	0.132282	0.008900	0.076861	0.004045	0.010113	0.047330	0.279935

There isn't any clear relationship between a voters house type and their voting rate, it is interesting to notice that voters living in Apartments seem a little more likely to be in the never voter category, however in the most recent election cycle they are also more likely to be in the always vote group!

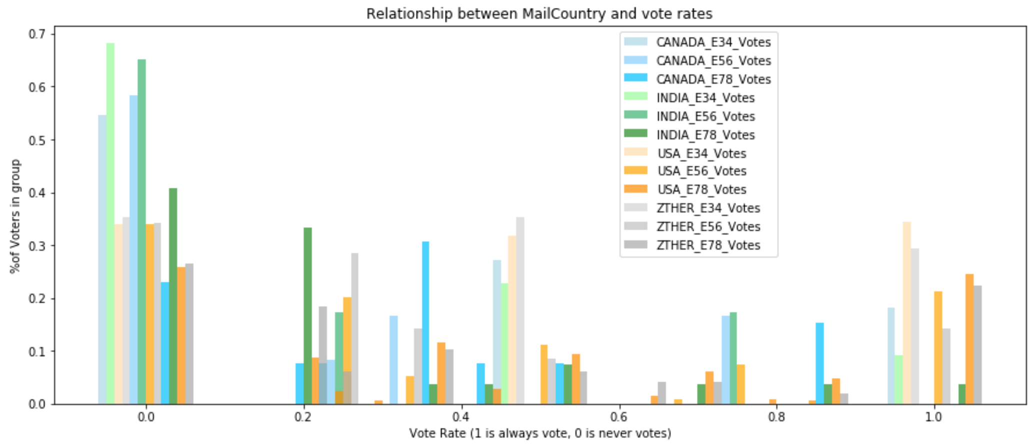
Exploring how MailCountry is related to voting behavior

In [35]:
```
df = vote_data_plus_fields(['MailCountry'])
for_other=['GERMANY', 'JAPAN', 'THAILAND', 'ISRAEL', 'PHILIPPINES', 'CHINA', 'MYANMAR',
           'HONG KONG','TAIWAN', 'AUSTRALIA', 'SERBIA', 'SINGAPORE', 'SPAIN','GHANA',
           'COSTA RICA', 'AUSTRIA', 'CHILE', 'LEBANON','GREECE', 'UNITED KINGDOM', 'MEXICO',
           'NEW ZEALAND','PAKISTAN', 'PERU', 'SWITZERLAND', 'ARGENTINA']
df['MC_Main'] = df.loc[df.MailCountry.notnull(),'MailCountry'].astype(str)
df.loc[df.MC_Main.isin(for_other) == True,['MC_Main']] = 'ZTHER'
df = df.drop('MailCountry', axis=1)

#df.MC_Main.value_counts()

dfm = []
df.groupby(['MC_Main']).describe()
for key, grp in df.groupby(['MC_Main']):
    dfm.append(vote_rate_as_pct(grp, key))
```

```
CANADA has:
    n = 11 for E34 data
    n = 12 for E56 data
    n = 13 for E78 data
INDIA has:
    n = 22 for E34 data
    n = 23 for E56 data
    n = 27 for E78 data
USA has:
    n = 233 for E34 data
    n = 253 for E56 data
    n = 329 for E78 data
ZTHER has:
    n = 34 for E34 data
    n = 35 for E56 data
    n = 49 for E78 data
```

In [36]:

```
title = 'Relationship between MailCountry and vote rates'
plot_always_never_only = False

if plot_always_never_only:
    # plot of always and never voters only:
    tdf = [d.loc[['0.0','1.0'],:] for d in dfm]
    plot_groups(tdf, title)
else:
    # plot of all vote rates:
    plot_groups(dfm, title)

pd.concat([d for d in dfm], axis=1, sort=True).transpose()
```



Out[36]:

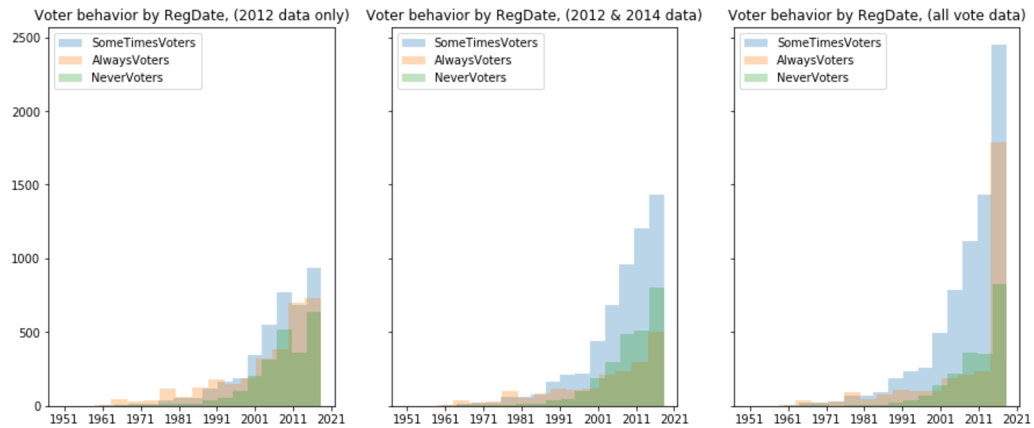
	0.0	0.17	0.2	0.25	0.33	0.4	0.5	0.6	0.67	0.75	0.8	0.83	1.0
CANADA_E34_Votes	0.545455	NaN	NaN	NaN	NaN	NaN	0.272727	NaN	NaN	NaN	NaN	NaN	0.181818
CANADA_E56_Votes	0.583333	NaN	NaN	0.083333	0.166667	NaN	NaN	NaN	NaN	0.166667	NaN	NaN	NaN
CANADA_E78_Votes	0.230769	0.076923	0.076923	NaN	0.307692	0.076923	0.076923	NaN	NaN	NaN	NaN	0.153846	NaN
INDIA_E34_Votes	0.681818	NaN	NaN	NaN	NaN	NaN	0.227273	NaN	NaN	NaN	NaN	NaN	0.090909
INDIA_E56_Votes	0.652174	NaN	NaN	0.173913	NaN	NaN	NaN	NaN	NaN	0.173913	NaN	NaN	NaN
INDIA_E78_Votes	0.407407	0.333333	NaN	NaN	0.037037	0.037037	0.074074	NaN	0.037037	NaN	NaN	0.037037	0.037037
USA_E34_Votes	0.339056	NaN	NaN	NaN	NaN	NaN	0.317597	NaN	NaN	NaN	NaN	NaN	0.343348
USA_E56_Votes	0.339921	NaN	NaN	0.201581	0.051383	NaN	0.110672	NaN	0.007905	0.075099	NaN	NaN	0.213439
USA_E78_Votes	0.258359	0.088146	0.024316	0.006079	0.115502	0.027356	0.094225	0.015198	0.060790	0.009119	0.006079	0.048632	0.246201
ZTHER_E34_Votes	0.352941	NaN	NaN	NaN	NaN	NaN	0.352941	NaN	NaN	NaN	NaN	NaN	0.294118
ZTHER_E56_Votes	0.342857	NaN	NaN	0.285714	0.142857	NaN	0.085714	NaN	NaN	NaN	NaN	NaN	0.142857
ZTHER_E78_Votes	0.265306	0.183673	0.061224	NaN	0.102041	NaN	0.061224	0.040816	0.040816	NaN	NaN	0.020408	0.224490

Voters with mailing address' outside the USA ie are actually voting from overseas, are more likely to end up in the never vote category. Particularly if your mailing address is in India you have between a 40 and 68% chance of being a never voter!

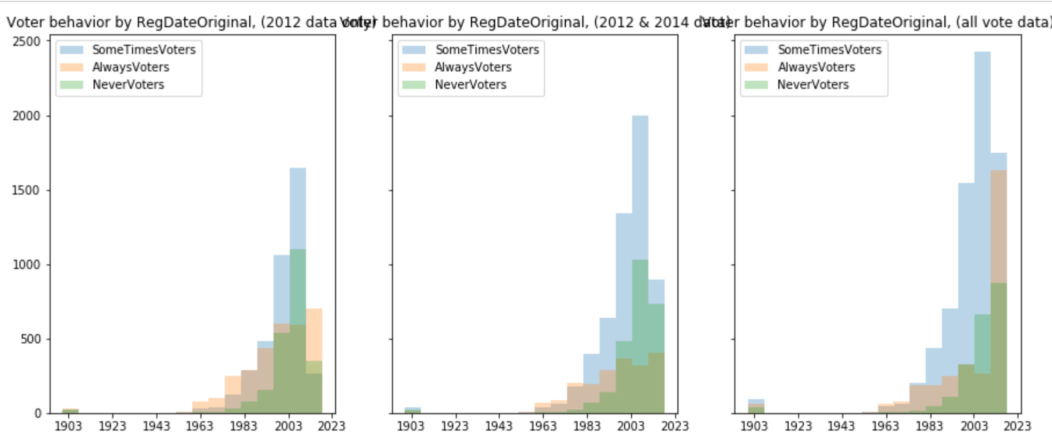
This data is on a very small sample size and so is not statistically robust.

Exploring how RegDate and RegDateOriginal affect vote behavior

In [37]:
```
df = vote_data_plus_fields(['RegDate'])

fig, (ax1,ax2,ax3) = plt.subplots(1,3, sharey=True)
ax1 = plot_hist_vote_rate_vs_field(ax1, df, 'E34_nVotesPct', 'RegDate')
ax1.set_title('Voter behavior by RegDate, (2012 data only)')

ax2 = plot_hist_vote_rate_vs_field(ax2, df, 'E56_nVotesPct', 'RegDate')
ax2.set_title('Voter behavior by RegDate, (2012 & 2014 data)')

ax3 = plot_hist_vote_rate_vs_field(ax3, df, 'E78_nVotesPct', 'RegDate')
ax3.set_title('Voter behavior by RegDate, (all vote data)')

plt.show()
```



In [38]:
```
df = vote_data_plus_fields(['RegDateOriginal'])

fig, (ax1,ax2,ax3) = plt.subplots(1,3, sharey=True)
ax1 = plot_hist_vote_rate_vs_field(ax1, df, 'E34_nVotesPct', 'RegDateOriginal')
ax1.set_title('Voter behavior by RegDateOriginal, (2012 data only)')

ax2 = plot_hist_vote_rate_vs_field(ax2, df, 'E56_nVotesPct', 'RegDateOriginal')
ax2.set_title('Voter behavior by RegDateOriginal, (2012 & 2014 data)')

ax3 = plot_hist_vote_rate_vs_field(ax3, df, 'E78_nVotesPct', 'RegDateOriginal')
ax3.set_title('Voter behavior by RegDateOriginal, (all vote data)')

plt.show()
```



Never voters seem to have slightly closer RegDates although this could just be the affect of age, a voter would need to be older to have an older regDate which we've already established is correlated with a greater chance of voting.