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 itertools
import matplotlib.pyplot as plt
import seaborn as sns

from IPython.display import display, Markdown
import statsmodels.stats.proportion as props
import scipy.stats as st

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

In [2]:
```
# load the data
households = load_households('data_clean/20180725_fullset_households_dis
trict3.csv')
voters = load_voters('data_clean/20180725_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_nVotesPctInH
H']
```

In [3]:
```
# a couple of constants
outcols = ['votes_s0','elec_n0','rate_r0','votes_s1','elec_n1','rate_r1'
,'emp_diff', 'calc_z', 'calc_p','perm_p']
perm_iterations = 10000
ap = {'arrowstyle':'->', 'color':'gray'}
```

Defining various methods and functions used to present the data.

In [4]:
```
def clean_df(df, fields, vrates):
    """
    Returns the voter rate columns with Nan not -1
    and fields in fields have missing values replaced with NaNs.
    """
    # 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[vrates]:
        df[c].replace(-1, np.NaN, inplace=True)

    return df
```

In [5]:
```
def show_vote_rate_and_summary(df, lab, title):
    """
    Draws the horizontal histograms for the data provided in df '_nVotes
Pct' in columns one per hist required.
    labels for each data column and a title are passed in and used.
    """
    vrs = df.columns
    n_plt = len(vrs)

    fig, axes = plt.subplots(n_plt, 1, sharex=True, figsize=(20,n_plt*2
))

    # Vote in every election, or 5/6 then you're in the top Always vote'
 category
    # Vote in 1/2, 2/4, 3/6, 3/5 or 2/5 then in the middle category
    # Vote in no election or 1/6 then in the bottom 'Never vote' categor
y
    edges = [0, 0.19, 0.39, 0.61, 0.81, 1]

    n = [0 for i in range(n_plt)]
    for i,(e,l) in enumerate(zip(vrs,lab)):
        # drawing the graph
        _ = axes[i].hist(df[e].dropna(), density=True, bins=edges, orien
tation='horizontal',
                              label=l, alpha=0.7)
        # calculating the bucket counts
        n[i], _ = np.histogram(df[e].dropna(), bins=edges)
    for i,ax in enumerate(axes):
        ax.legend(loc='center right')
        ax.annotate('Voters who always Vote', xy=[1,0.8], xytext=[1.1,0.
61], arrowprops=ap, color='gray')
        ax.annotate('Voters who never Vote', xy=[1,0.2], xytext=[1.1,0.2
9], arrowprops=ap, color='gray')

    ylab = 'Vote Rate in last 6 elections'
    axes[n_plt-1].set_xlabel('Probability Density Function (PDF)')
    _ = axes[0].set_title(title)
    _ = axes[0].set_ylabel(ylab)
    _ = axes[0].yaxis.set_label_coords(-0.03, -0.05*n_plt)
    plt.show()

    # calculating and displaying the summary table
    order =['Never','Under Half','Half','Over Half','Always']
    dw = pd.DataFrame(n, columns=order, index=lab).transpose()
    dw2 = pd.DataFrame()
    for e in lab:
        dw2[e+'_pct'] = round(dw[e]/sum(dw[e]),3) * 100
    dw = pd.concat([dw, dw2], keys=('Number of Voters','Voters as a %'),
 axis=1)
    dw = dw.loc[order[::-1],:]
    dw.loc['Totals'] = dw.sum(axis=0)
    dw['Number of Voters'] = dw['Number of Voters'].astype('int')
    display(dw)
    return dw
```

In [6]:
```
def plot_hist_vote_rate_vs_field(ax, df, voteRatef, field, bins):
    """
    Spliting the provided data into sometimes, always and never voters a
nd drawing
    a histogram of the three vote categories on the provided axis.
    """
    a, b = 0.3, bins
    df1 = pd.DataFrame(df[[voteRatef, field]]).rename(columns = {voteRat
ef:'VR'})
    always, sometimes, never, allv = (df1.VR == 1), (df1.VR < 1) & (df1.
VR > 0), (df1.VR == 0), (df1.VR.notnull())

    rs,_,_ = ax.hist(df1.loc[sometimes, field], bins=b, alpha=a, label=
'SomeTimesVoters')
    ra,_,_ = ax.hist(df1.loc[always, field], bins=b, alpha=a, label='Alw
aysVoters')
    rn,_,_ = ax.hist(df1.loc[never, field], bins=b, alpha=a, label='Neve
rVoters')
    rt,_,_ = ax.hist(df1.loc[allv, field], bins=b, alpha=a, label='Total
 #', histtype='step')

    ax.legend(loc='upper left')
    return ax,[ra,rs,rn,rt]
```

In [7]:
```
def draw_bs_reps(data, func, size=1):
    """Draw bootstrap replicates."""
    bs_replicates = np.empty(size)
    for i in range(size):
        bs_replicates[i] = func(np.random.choice(data, size=len(data)))
    return bs_replicates

def ecdf(data):
    """Compute ECDF for a one-dimensional array of measurements."""
    n = len(data)
    x = np.sort(data)
    y = np.arange(1, n+1) / n
    return x, y
```

```
In [8]: def bs_ts_diff_of_means_test(d1, d2):
    """
    Run a bootstrap diff of means test between the two provided datafram
es
    ploting an ecdf and histogram of the bootstrap replicates created
    """
    fig, (ax1,ax2) = plt.subplots(1,2, figsize=(20,3))

    # Compute values for and plot ECDFs
    x_d1, y_d1 = ecdf(d1)
    x_d2, y_d2 = ecdf(d2)
    ax1.plot(x_d1, y_d1, marker='.', linestyle='none')
    ax1.plot(x_d2, y_d2, marker='.', linestyle='none')

    # Label and show plot
    ax1.margins(0.02)
    ax1.legend(('always vote', 'never vote'), loc='lower right')
    ax1.set_xlabel('age of voter')
    ax1.set_ylabel('ECDF')

    # Compute the difference in two samples
    diff_means = np.mean(d1) - np.mean(d2)
    print('Empirical difference in mean age observed: {:.0f}-{:.0f}={:.
3} years'.format(
        np.mean(d1),np.mean(d2),diff_means))

    # Compute mean of pooled data: mean_count
    mean_count = np.mean(np.concatenate((d1, d2)))

    # Generate shifted data sets
    av_shifted = d1 - np.mean(d1) + mean_count
    nv_shifted = d2 - np.mean(d2) + mean_count

    # Generate bootstrap replicates using shifted data
    bs_reps_av = draw_bs_reps(av_shifted, np.mean, size=10000)
    bs_reps_nv = draw_bs_reps(nv_shifted, np.mean, size=10000)

    # Get replicates of difference of means: bs_replicates
    bs_replicates = bs_reps_av - bs_reps_nv

    _ = ax2.hist(bs_replicates, density=True, bins=100)
    _ = ax2.axvline(diff_means, color='red')
    _ = ax2.set_xlabel('Test-statistic ({})'.format('Diff of means'))
    _ = ax2.set_ylabel('PDF')
    plt.show()

    # Compute and print p-value: p
    p = np.sum(bs_replicates <= np.mean(d1) - np.mean(d2))/ len(bs_repli
cates)
    print('p-value =', p)
```

In [9]:
```
def get_two_sample_ns(d0,d1):
    """
    Calculate the number of elections and successes as well as the perce
nt success rate
    for the two provided dataframes. '_nVotesPos' and '_nVotes' columns
 are expected.
    """
    nVotesPos = [c for c in d0.columns if 'nVotesPos' in c][0]
    nVotes = nVotesPos[:-3]
    n0, s0 = d0[nVotesPos].sum(), d0[nVotes].sum()
    n1, s1 = d1[nVotesPos].sum(), d1[nVotes].sum()
    return s0,n0,(100*s0/n0),s1,n1,(100*s1/n1)
```

In [10]:
```
def diff_frac_votes(d0, d1):
    """Compute the difference in fraction of votes.
    Input two data frames with the nVotesPos and nVotes fields for elect
ion(s) of interest"""
    [s0,n0,_,s1,n1,_] = get_two_sample_ns(d0, d1)
    #print('diff frac votes:{}'.format((s0 / n0) - (s1 / n1)))
    return (s0 / n0) - (s1 / n1)

def permutation_sample(data1, data2):
    """Generate a permutation sample from two data sets."""
    data = pd.concat((data1, data2))
    permuted_data = data.sample(frac=1)
    return permuted_data[:len(data1)], permuted_data[len(data1):]

def draw_perm_reps(data_1, data_2, func, size=1):
    """Generate multiple permutation replicates."""
    perm_replicates = np.empty(size)
    for i in range(size):
        perm_sample_1, perm_sample_2 = permutation_sample(data_1, data_2
)
        # Compute the test statistic
        perm_replicates[i] = func(perm_sample_1, perm_sample_2)
    return perm_replicates
```

In [11]:
```
def two_sample_perm_test_diff_frac_votes(d0, d1, ax, lbl, tail=1):
    """Complete a two sample permutation test using difference in fracti
on of votes as test statistic"""

    # Compute the test statistic from experimental data: empirical_diff_
means
    empirical_diff_frac_votes = diff_frac_votes(d0, d1)

    # Draw 10,000 permutation replicates: perm_replicates
    perm_replicates = draw_perm_reps(d0, d1, diff_frac_votes, size=perm_
iterations)

    # Plot test statistic histogram
    _ = ax.hist(perm_replicates, density=True, bins=1000)
    _ = ax.axvline(empirical_diff_frac_votes, color='red')
    _ = ax.set_xlabel('Difference in vote rate for category')
    _ = ax.set_ylabel('PDF')
    _ = ax.set_title('For {}'.format(lbl))

    # Compute p-value: p
    p = np.sum(perm_replicates >= empirical_diff_frac_votes) / len(perm_
replicates)
    if p >0.5:
        p = 1-p

    lmt = 0.01 if tail == 1 else 0.005
    [nn_ll, nn_ul] = np.percentile(perm_replicates, [lmt*100,(1-lmt)*100
])

    _ = ax.axvline(nn_ll, color='orange', ls='--')
    _ = ax.axvline(nn_ul, color='orange', ls='--')

    ar_ht = ax.get_ylim()[1]*0.9
    tx_x = -np.abs(nn_ul)+0.5*np.std(perm_replicates)
    text = '{} tail 99% Conf ({:.3f} : {:.3f})'.format(tail, nn_ll, nn_u
l)
    ax.annotate(text, xy=[nn_ul,ar_ht*0.7], xytext=[tx_x,ar_ht], color=
'w', alpha=0, arrowprops=ap)
    ax.annotate(text, xy=[nn_ll,ar_ht*0.7], xytext=[tx_x,ar_ht], color=
'gray', arrowprops=ap)

    return p, empirical_diff_frac_votes, ax
```

All Voters in our dataset

In [12]:
```
display(Markdown('Our data covers one district, containing information a
bout **{}** 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, the vote rate was Calculated on a scale of 0-1. Our data lets us know if a particular voter was registered to vote in a particular election (ie could have possibly voted) and then also if they did actually vote in that election. If a voter voted in all elections they could have voted in then their vote rate is 1 and they 'always' voted, if they didn't vote in any of the elections they were registered for then their vote rate is 0 and they 'never' voted, numbers in between indicate that the voter voted in some of the elections they could have done but not all of them, higher is more likely.

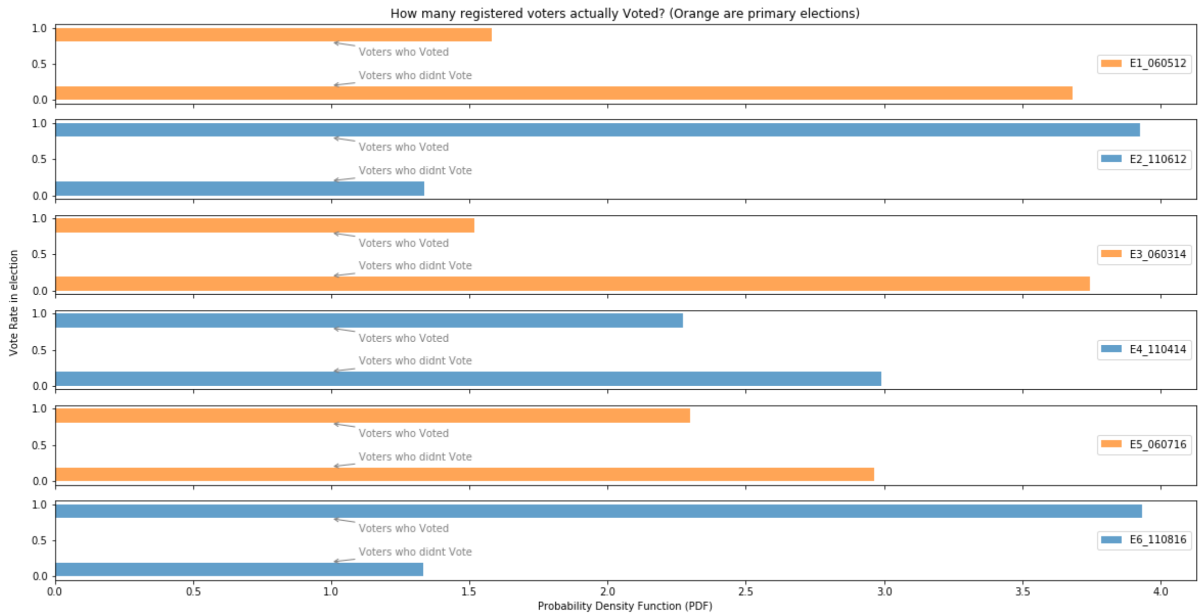
We have data on 6 elections:

- E1 the primary held on 5^{th} June 2012
- E2 the general held on 6^{th} November 2012 - this was a presidential election
- E3 the primary held on 3^{rd} June 2014
- E4 the general held on 4^{th} November 2014 - this was a congressional election
- E5 the primary held on 7^{th} June 2016
- E6 the general held on 8^{th} November 2016 - this was a presidential election

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.

Single elections - How many people vote?

In [13]:
```
ev = ['E1_nVotesPct','E2_nVotesPct','E3_nVotesPct','E4_nVotesPct','E5_nV
otesPct','E6_nVotesPct']
lab = ['E6_110816', 'E5_060716','E4_110414', 'E3_060314', 'E2_110612',
'E1_060512']

df_e = clean_df(voters.loc[:,ev],[],ev)

fig, axes = plt.subplots(6,1, sharex=True, figsize=(20,10))
edges = [0, 0.19, 0.39, 0.61, 0.81, 1]

n = [0 for i in range(6)]
for i,(e,l) in enumerate(zip(ev,lab[::-1])):
    col = 'tab:blue' if '11' in l else 'tab:orange'
    # drawing the graph
    _ = axes[i].hist(df_e[e].dropna(), density=True, bins=edges, orienta
tion='horizontal',
                     label=l, alpha=0.7, color=col)
    # calculating the bucket counts
    n[i], _ = np.histogram(df_e[e].dropna(), bins=edges)

ap = {'arrowstyle':'->', 'color':'gray'}
for i,ax in enumerate(axes):
    ax.legend(loc='center right')
    ax.annotate('Voters who Voted', xy=[1,0.8], xytext=[1.1,0.61], arrow
props=ap, color='gray')
    ax.annotate('Voters who didnt Vote', xy=[1,0.2], xytext=[1.1,0.29],
arrowprops=ap, color='gray')

title = 'Vote Rate in election'
axes[5].set_xlabel('Probability Density Function (PDF)')
_ = axes[0].set_title('How many registered voters actually Voted? (Orang
e are primary elections)')
_ = axes[0].set_ylabel(title)
_ = axes[0].yaxis.set_label_coords(-0.03, -2.5)
plt.show()

# calculating and displaying the summary table
order =['Skipped','Under Half','Half','Over Half','Voted']
dw = pd.DataFrame(n, columns=order, index=lab[::-1]).transpose()
dw2 = pd.DataFrame()
for e in lab[::-1]:
        dw2[e[:2]+'_pct'] = round(dw[e]/sum(dw[e]),3) * 100
dw = pd.concat([dw, dw2], keys=('Number of Voters','Voters as a %'), axi
s=1)
#dw = dw.drop(dw[dw.sum(axis='columns') <1].index)
dw = dw.loc[['Voted', 'Skipped'],:]
dw.loc['Totals'] = dw.sum(axis=0)
dw['Number of Voters'] = dw['Number of Voters'].astype('int')
dw
```



Out[13]:

	Number of Voters						Voters as
	E1_060512	**E2_110612**	**E3_060314**	**E4_110414**	**E5_060716**	**E6_110816**	**E1_pct**
Voted	2577	6937	2807	4314	4846	9220	30.0
Skipped	6000	2359	6920	5673	6255	3122	70.0
Totals	8577	9296	9727	9987	11101	12342	100.0

Looking at these graphs you can see we get highest turnout $\approx 70\%$ of registered voters for presidential General elections, while only seeing a $\approx 43\%$ turnout for the congressional general election in 2014.

Primaries have a much lower vote rate that their general elections $\approx 28 - 43\%$ although we saw a large turnout for the most recent 2016 primary 43.7%, in fact it was just larger than the prior congressional year general election 43.2%!

Are they representative?

In order to validate our observed data I decided to run a two tailed one sample Z test comparing our observed vote rate to that published by the US Census Bureau for the 2016 Presidential Election. Date available here (https://www.census.gov/newsroom/blogs/random-samplings/2017/05/voting_in_america.html) reports that 61.4% of voting-age population reported voting.

Statistically testing with a one sample z test (calculated using proportions_ztest())

- Null hypothesis: our observed vote rate is the same as the reported rate of 61.4%
- Alt hypothesis: our observation is different

alpha = 0.01

In [14]:
```
n, s = voters.E6_nVotesPos.sum(), voters.E6_nVotes.sum()
display(Markdown('Our observed vote rate is: ${} / {}={:.0f}\%$'.format(
s,n,100*s/n)))
(z, p) = props.proportions_ztest(s, n, value=0.614, alternative='two-sid
ed')
display(Markdown('Test statistic (calculated using proportions_ztest()):
 ${:.4}$'.format(z)))
display(Markdown('P value: ${:.6}$'.format(p)))
```

Our observed vote rate is: $9220/12342 = 75\%$

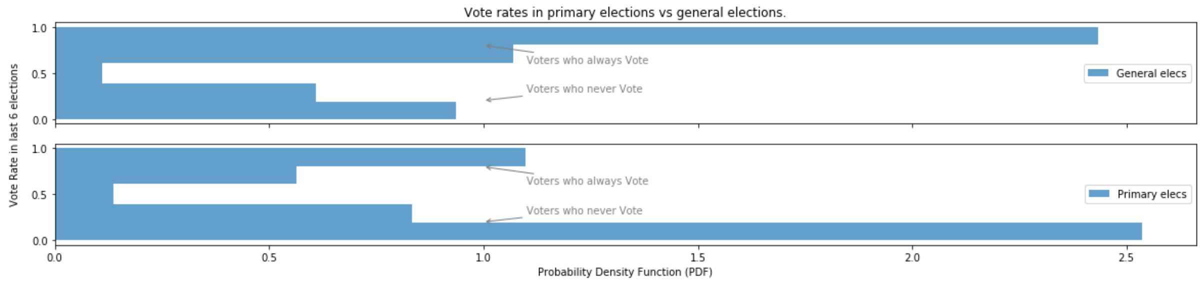
Test statistic (calculated using proportions_ztest()): 34.0

P value: $2.17925e-253$

This tiny p value is way below the 99% confidence level I selected so I must reject the null hypothesis and conclude that it is highly unlikely that the voters in my particular district are representative of the general US voting population at large. This is not really a surprising result given the geographical co-location of my data. Lets see what other voting characteristics do hold.

Over all how much more do people vote in General elections than Primaries?

```
In [15]: vrs = ['Eag_nVotesPct','Eap_nVotesPct',]
df_w = clean_df(voters.loc[:,vrs], [], vrs)
title = 'Vote rates in primary elections vs general elections.'
df = show_vote_rate_and_summary(df_w, ['General elecs','Primary elecs'],
 title)
```



	Number of Voters		Voters as a %	
	General elecs	**Primary elecs**	**General elecs_pct**	**Primary elecs_pct**
Always	5725	2334	46.3	20.9
Over Half	2647	1260	21.4	11.3
Half	298	337	2.4	3.0
Under Half	1506	1862	12.2	16.7
Never	2200	5384	17.8	48.2
Totals	12376	11177	100.1	100.1

Is this a real difference?

I'm going to calculate statistical significance using the number of possible votes cast across the elections of interest as our total n and the proportion of those where votes were in fact cast as the success proportion or s. This will ensure that we keep a direct link between success' and n number of trials when calculating our p values.

I've calculated statistical significance with two tests - the first a automated two sample proportion ztest (props.proportions_ztest()) - this test is possibly not appropriate to use as our sample size is larger than 10% of the total population. So I also calculated an estimated p based on a two sample permutation test.

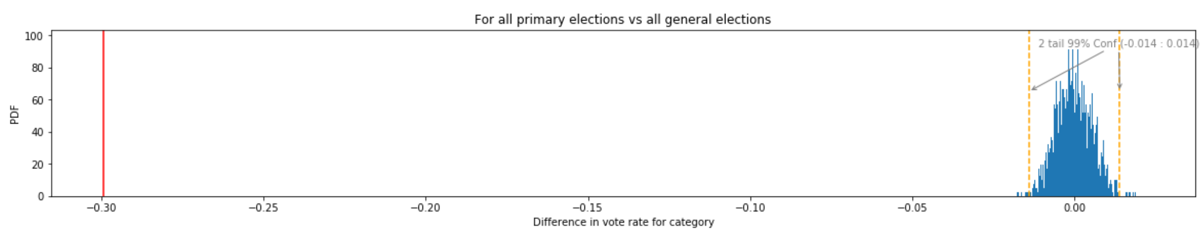
- Null hypothesis: the true vote rate for primaries and general elections is actually the same
- Alt hypothesis: the vote rates are different

Significance level: 0.01 or 99% confidence

The zero p-value from both tests shown below requires us to reject the null hypothesis. Our data strongly supports that the underlying voter rate is lower in primary elections than general elections.

```
In [16]: dx = voters[['Eap_nVotesPos', 'Eap_nVotes']]
dy = voters[['Eag_nVotesPos', 'Eag_nVotes']].rename(columns={'Eag_nVotes
Pos':'Eap_nVotesPos',
                                                              'Eag_nVote
s':'Eap_nVotes'})
fig, axes = plt.subplots(figsize=(20,3))

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all primary el
ections vs all general elections', tail=2)
df.loc['All primary vs general elections',outcols] = [sx,nx,rx,sy,ny,ry,
emp_diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	calc_
All primary vs general elections	10230	29405	34.79	20471	31625	64.7304	-29.9404	-73.918	0



How does Age affect vote rate (aka BirthYear)

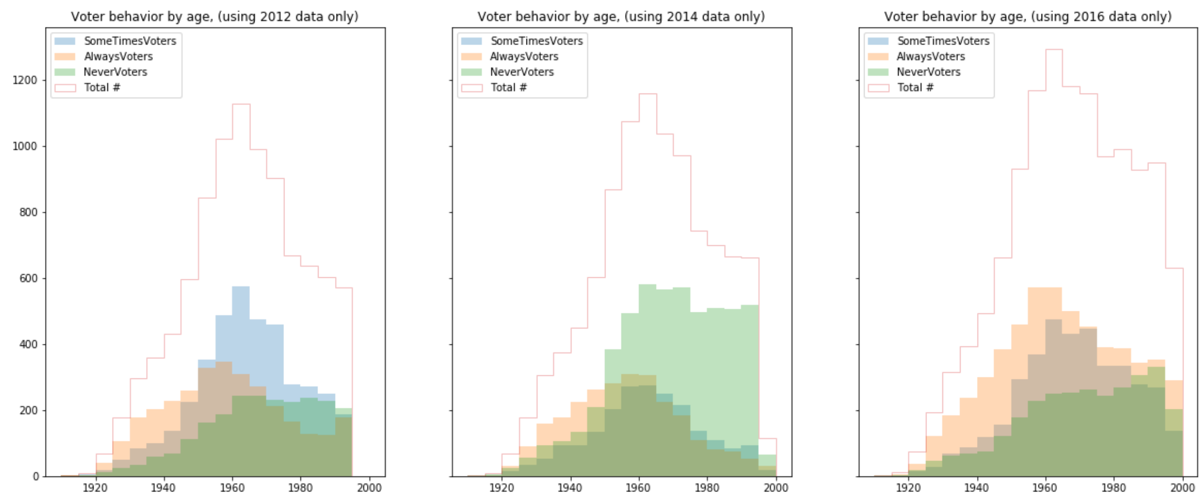
In [17]:
```
vs, f = ['E12_nVotesPct','E14_nVotesPct','E16_nVotesPct'],['BirthYear']
df = clean_df(voters.loc[:,vs + f], f, vs)

old = df.BirthYear < 1901
young = df.BirthYear > 1995
#print(df[old | young].BirthYear.value_counts().sort_index())
display(Markdown('There are {} people over 100 (inc {} people entering 1
900 which is likely bad data)'.format(
df[df.BirthYear < 1918].BirthYear.count(),df[df.BirthYear == 1900].Birth
Year.count())))
display(Markdown('As you would expect some people ({}) register as they
 turn 18'.format(
df[df.BirthYear == 2000].BirthYear.count())))

display(Markdown('\nThe {} voters who have 1900 entered for their BirthY
ears 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 [18]: fig, (ax1,ax2,ax3) = plt.subplots(1,3, sharey=True, figsize=(20,8))
         d = [0 for i in range(3)]
         bins = [c for c in range(1910, 2001, 5)]

         ax1, d[0] = plot_hist_vote_rate_vs_field(ax1, df, 'E12_nVotesPct', 'BirthYear', bins)
         ax1.set_title('Voter behavior by age, (using 2012 data only)')

         ax2, d[1] = plot_hist_vote_rate_vs_field(ax2, df, 'E14_nVotesPct', 'BirthYear', bins)
         ax2.set_title('Voter behavior by age, (using 2014 data only)')

         ax3, d[2] = plot_hist_vote_rate_vs_field(ax3, df, 'E16_nVotesPct', 'BirthYear', bins)
         ax3.set_title('Voter behavior by age, (using 2016 data only)')

         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. This is a particularly strong effect in the Congressional year of 2014.

You can also see that the young are less likely to have registered to vote in the first place as the total voter histograms all show a peak around birth year 1960. Its also possible that this effect is caused not by younger voters not registering but by our district having fewer younger voters living here. It is also plausible that younger voters are more mobile and so even if they were here for the 2012 or 2014 vote they have since moved out of the district and so dropped out of our data set and you can't forget that there may just be more people born in the 1960's.

Is this a real difference?

Statistically testing with a bootstrapped two sample test of the means of each group, I'm using bootstrapping as it avoids the issue of our sample being more than 10% of the total population of our district.

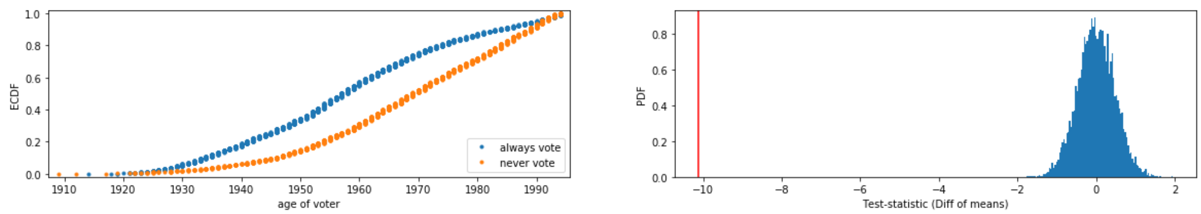
- Null hypothesis: the average age of never voters and always voters is the same
- Alt hypothesis: the average age of never voters is lower than the average of always voters

Significance level: 0.01

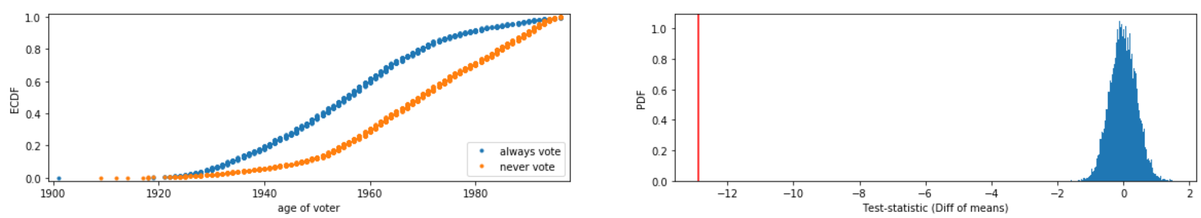
The zero p-value shown below requires us to reject the null hypothesis. Our data strongly supports that the average age of never voters is lower than the average age of always voters rate.

In [19]:
```
years = [('E12','2012'),('E14','2014'),('E16','2016')]
for (y, lbl) in years:
    d1 = df.loc[(df[y + '_nVotesPct'] == 1),['BirthYear']].BirthYear
    d2 = df.loc[(df[y + '_nVotesPct'] == 0),['BirthYear']].BirthYear
    print('\nCalculating p-value for difference in mean age of voters du
ring {}\n'.format(lbl))
    bs_ts_diff_of_means_test(d1,d2)
```

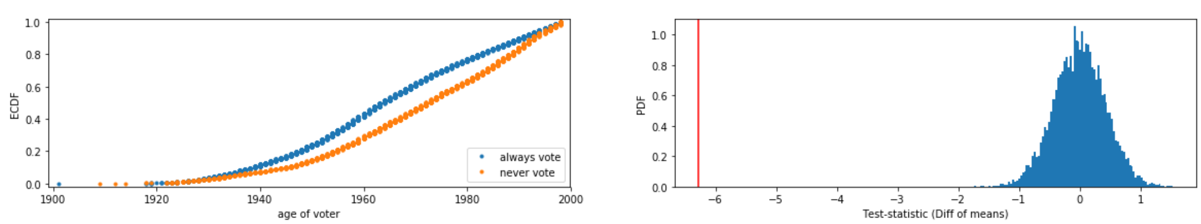
```
Calculating p-value for difference in mean age of voters during 2012

Empirical difference in mean age observed: 1958-1968=-10.1 years
```




```
p-value = 0.0

Calculating p-value for difference in mean age of voters during 2014

Empirical difference in mean age observed: 1956-1969=-12.9 years
```



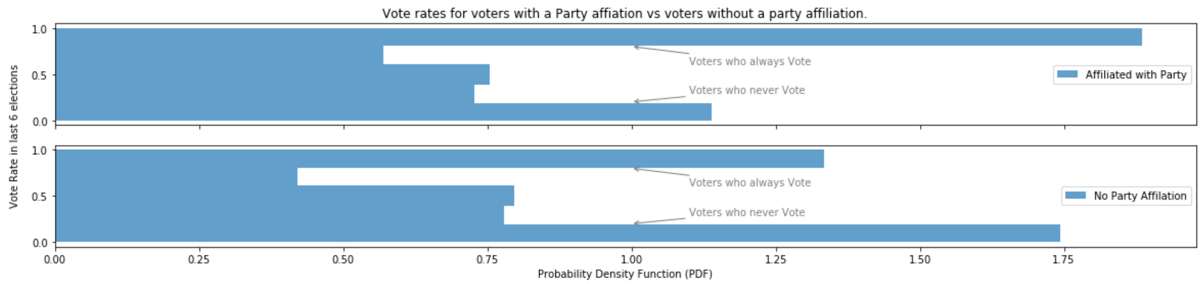

```
p-value = 0.0

Calculating p-value for difference in mean age of voters during 2016

Empirical difference in mean age observed: 1964-1971=-6.29 years
```




```
p-value = 0.0
```

Grouping the voters by hasParty

```
In [20]: vs, f = ['E78_nVotesPct'],['HasParty']
df_w = clean_df(voters.loc[:,vs + f], f, vs)
( _, d1 ), ( _, d0 ) = df_w.groupby(['HasParty'])
df_w = pd.DataFrame({'HasParty':d0[vs[0]],'NoParty':d1[vs[0]]})
title = 'Vote rates for voters with a Party affiation vs voters without
 a party affiliation.'
df = show_vote_rate_and_summary(df_w, ['Affiliated with Party','No Party
 Affilation'], title)
```



	Number of Voters		Voters as a %	
	Affiliated with Party	No Party Affilation	Affiliated with Party_pct	No Party Affilation_pct
Always	3074	962	35.8	25.4
Over Half	977	319	11.4	8.4
Half	1426	665	16.6	17.5
Under Half	1248	591	14.5	15.6
Never	1859	1257	21.7	33.1
Totals	8584	3794	100.0	100.0

You can see that blue (noParty) bars are taller on the never vote row while the (hasParty) bars are taller on the always vote row. 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 ~12% less likely to be a never voter.

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

Is this a real effect?

Statisticaly testing with a two sample z test (calculated using proportions_ztest()) and with a permutation test. The permutation test is likely more appropriate as we have a sample size that is over 10% of the total population.

- H0: The vote rate of people with a party affiliation matches that of those without (the difference in vote proportion is 0)
- Ha: The vote rate of people without a party affiliation is lower than those affiliated

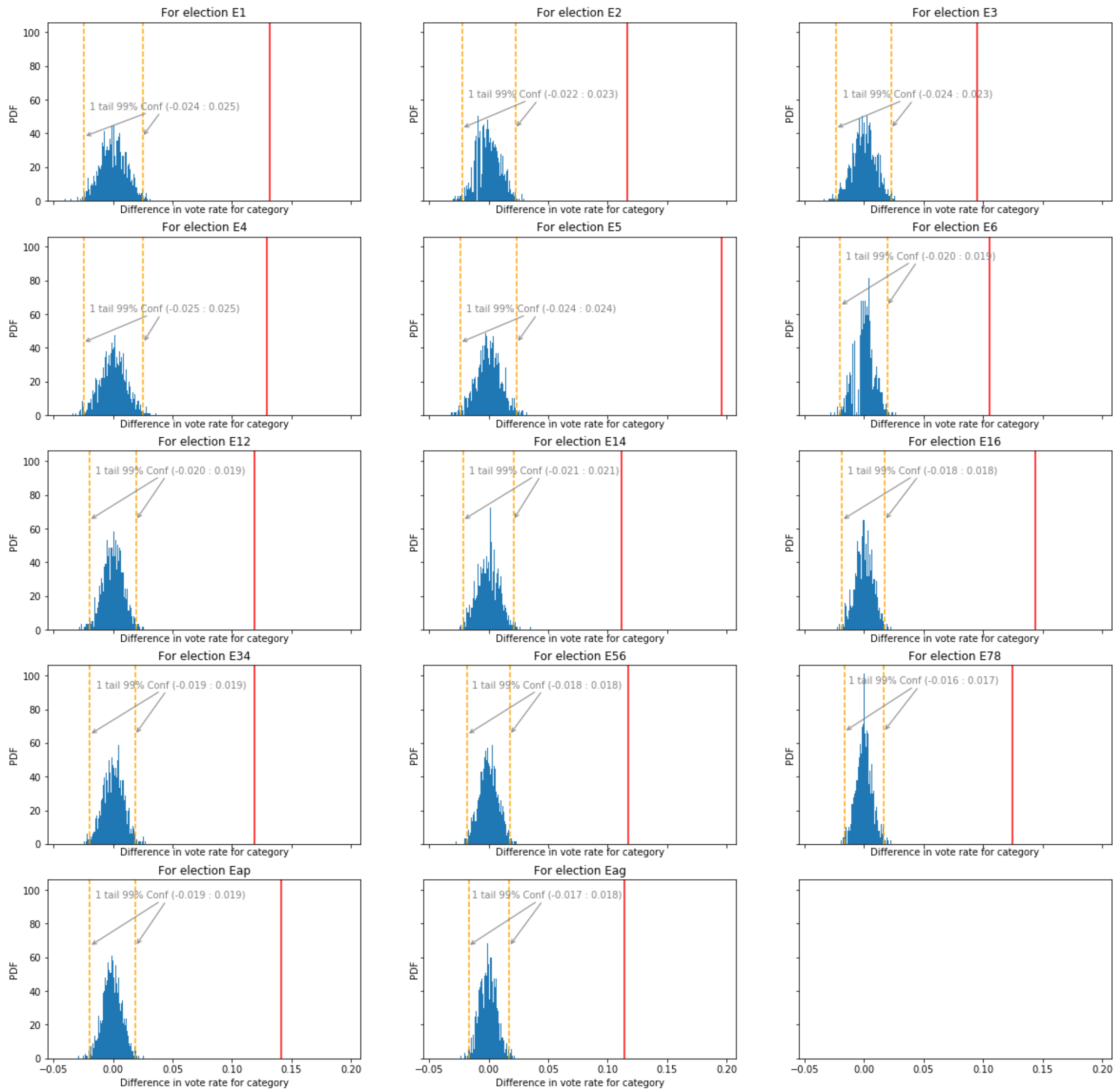
Alpha = 0.01

I calculated these test scores for every election and combination of election. In each case the p-values indicated that we need to reject the null hypothesis. The link between vote rate difference we observe between having and not having a party affiliation is extremely unlikely to occur by chance alone. Having a party affiliation makes you more likely to vote. This effect was strong and held across all combinations of election tested.

In [21]:

```
election_combs = ['E1','E2','E3','E4','E5','E6','E12','E14', 'E16', 'E3
4','E56','E78','Eap','Eag']
layout = [(i,j) for i in range(5) for j in range(3)]

fig, axes = plt.subplots(5,3,figsize=(20,20), sharex=True, sharey=True)

df = pd.DataFrame(columns=outcols)

for i,(e,loc) in enumerate(zip(election_combs,layout)):
    #display(Markdown('Processing **{}**...'.format(e)))
    vs, f = [e+'_nVotesPos',e+'_nVotes'],['HasParty']
    df_w = clean_df(voters.loc[:,vs + f], f, vs)
    (_, d1), (_, d0) = df_w.groupby(['HasParty'])
    s0,n0,r0,s1,n1,r1 = get_two_sample_ns(d0, d1)
    cz,cp = props.proportions_ztest([s0,s1], [n0,n1], alternative='large
r')
    pp, emp_diff, axes[loc] = two_sample_perm_test_diff_frac_votes(d0,d1
,axes[loc],'election '+e, tail=1)
    #display(Markdown('Empirical difference: **${:.2f}\%$**, Perm test e
stimated P-value: {}'.format(emp_diff*100,p)))
    df.loc[e,outcols] = [s0,n0,r0,s1,n1,r1,emp_diff*100,cz,cp,pp]

df.rename(columns ={'votes_s0':'v_hasP', 'elec_n0':'n_hasP', 'rate_r0':
'rate_hasParty',
                       'votes_s1':'v_noP', 'elec_n1':'n_noP', 'rate_r1':
'rate_noParty'}, inplace=True)
df = df.rename(index = {'E1':'E1_060512','E2':'E2_110612','E3':'E3_06031
4',
                     'E4':'E4_110414','E5':'E5_060716','E6':'E6_110816',
                     'E12':'2012 (P&G)','E14':'2014 (P&G)', 'E16':'2016
 (P&G)', 'E34':'2012 again','E56':'12,&14','E78':'12,14,&16',
                     'Eap':'All Primary','Eag':'All General'})
display(df)
plt.show()
```

	v_hasP	n_hasP	rate_hasParty	v_noP	n_noP	rate_noParty	emp_diff	calc_z
E1_060512	2099	6244	33.6163	478	2333	20.4886	13.1276	11.800
E2_110612	5214	6695	77.879	1723	2601	66.2438	11.6353	11.572
E3_060314	2193	6946	31.5721	614	2781	22.0784	9.49374	9.3372
E4_110414	3332	7101	46.923	982	2886	34.0263	12.8966	11.793
E5_060716	3868	7823	49.4439	978	3278	29.8353	19.6087	19.002
E6_110816	6671	8559	77.9413	2549	3783	67.3804	10.561	12.443
2012 (P&G)	7313	12939	56.5191	2201	4934	44.6088	11.9102	14.266
2014 (P&G)	5525	14047	39.3322	1596	5667	28.163	11.1692	14.775
2016 (P&G)	10539	16382	64.3328	3527	7061	49.9504	14.3824	20.622
2012 again	7313	12939	56.5191	2201	4934	44.6088	11.9102	14.266
12,&14	12838	26986	47.5728	3797	10601	35.8174	11.7554	20.647
12,14,&16	23377	43368	53.9038	7324	17662	41.4676	12.4362	27.865
All Primary	8160	21013	38.8331	2070	8392	24.6663	14.1668	23.033
All General	15217	22355	68.0698	5254	9270	56.6775	11.3923	19.300

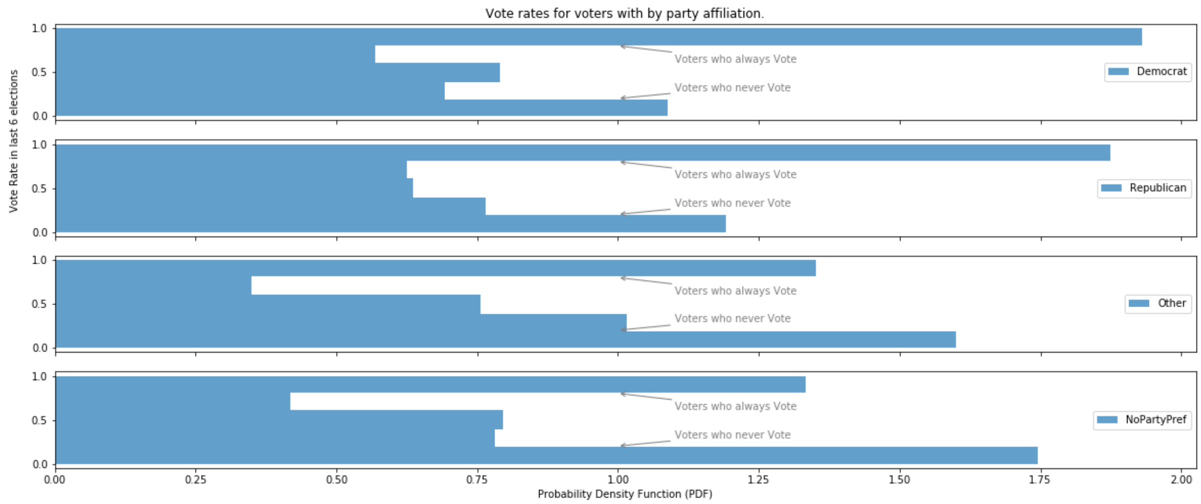


Grouping by PartyMain

In [22]:

```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['PartyMain']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

```
In [23]: # Summarize data
(k3, d3), (k2, d2), (k1, d1), (k0, d0) = df_g.groupby(['PartyMain'])
df_w = pd.DataFrame({k3:d3[vs[0]], k0:d0[vs[0]], k1:d1[vs[0]], k2:d2[vs[
0]]})
title = 'Vote rates for voters with by party affiliation.'
df = show_vote_rate_and_summary(df_w, ['Democrat','Republican','Other',
'NoPartyPref'], title)
```



	Number of Voters				Voters as a %		
	Democrat	Republican	Other	NoPartyPref	Democrat_pct	Republican_pct	Othe
Always	2285	664	125	958	36.7	35.6	25.7
Over Half	710	233	34	316	11.4	12.5	7.0
Half	1084	261	81	662	17.4	14.0	16.6
Under Half	864	285	99	591	13.9	15.3	20.3
Never	1289	422	148	1254	20.7	22.6	30.4
Totals	6232	1865	487	3781	100.1	100.0	100.(

You can see clearly that having a party preference of one of the two main parties increases your likelihood of always voting. 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, 33% of NPP voters never vote.

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.

Is this a real effect?

I used the same two tests as with the has_party analysis, an automated 2 sample z test and a two sample permutation test.

I analyzed the data for all the elections combined, and calculated statistical significant of each of the 4 main party groups against each other. So testing the following and its combinations with different party REP, DEM, OTH, NPP:

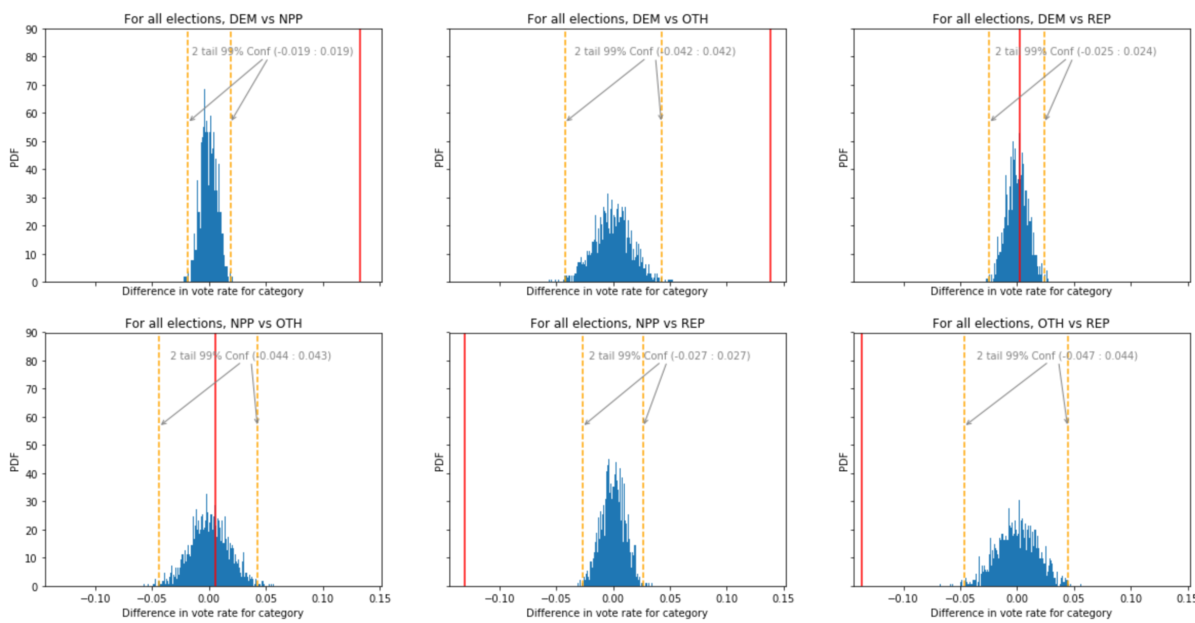
- H0: The vote rate of people affiliated with the DEM matches that of those affiliated with the REP (the difference in vote proportion is 0)
- Ha: The vote rate of people affiliated with the DEM is lower or higher than that of those affiliated with the REP

Alpha = 0.01

I tested each of the 4 main party groups (DEM, REP, OTH, NPP) against each other a total of 6 tests.

In [24]:
```
# Run Stats
g3, g2, g1, g0 = df_s.groupby(['PartyMain'])
party_combos = itertools.combinations([g3,g2,g1,g0], 2)
layout = [(i,j) for i in range(4) for j in range(3)]
fig, axes = plt.subplots(2,3,figsize=(20,10), sharex=True, sharey=True)

df = pd.DataFrame(columns=outcols)

for ((kx,dx),(ky,dy)),loc in zip(party_combos,layout):
    #display(Markdown('Processing **{} & {}**...'.format(kx, ky)))
    sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
    cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-s
ided')
    pp, emp_diff, axes[loc] = two_sample_perm_test_diff_frac_votes(dx,dy
,axes[loc],
                                                                  'all e
lections, {} vs {}'.format(kx,ky), tail=2)
    df.loc['All elections '+kx+':'+ky,outcols] = [sx,nx,rx,sy,ny,ry,emp_
diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	ca
All elections DEM:NPP	16858	30828	54.6841	7291	17609	41.405	13.2791	28.1159	6.2 17
All elections DEM:OTH	16858	30828	54.6841	937	2294	40.8457	13.8384	12.8243	1.1 37
All elections DEM:REP	16858	30828	54.6841	5582	10246	54.4798	0.204256	0.359786	0.7
All elections NPP:OTH	7291	17609	41.405	937	2294	40.8457	0.559279	0.511654	0.6
All elections NPP:REP	7291	17609	41.405	5582	10246	54.4798	-13.0748	-21.1061	6.9 99
All elections OTH:REP	937	2294	40.8457	5582	10246	54.4798	-13.6341	-11.8148	3.2 32



This is a two tail test so any p-value with a magnitude of < 0.05 would require us to reject the null hypothesis. In this case although the two tests are providing slightly different p-value estimates they agree on which hypothesis we have to reject and which we fail to reject.

We fail to reject in the following cases:

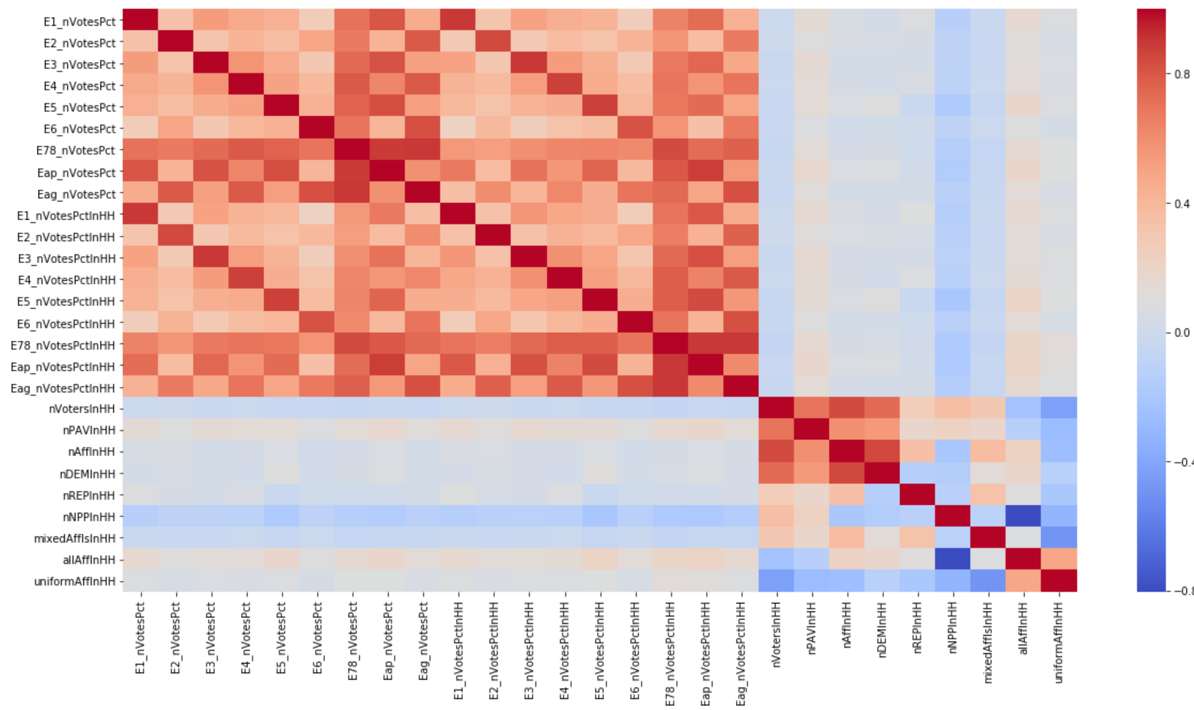
- DEM vs REP - the vote rate of someone affiliated with the Republicans is not statistically different from the vote rate for someone affiliated with the Democrats.
- NPP vs OTH - the vote rate of someone affiliated with the No Party is not statistically different from the vote rate for someone affiliated with one of the small parties.

We reject the null hypothesis in all the other cases, Our data indicates that with 99% confidence the vote rate of someone belonging to one of the two main parties (REP or DEM) is Significantly higher than the vote rate of someone belonging to one of the minor parties or holding No Party Preference.

Full Correlation Matrix of Household characteristics

In [25]:
```
#election_combos = ['E1','E2','E3','E4','E5','E6','E12','E14', 'E16', 'E
34','E56','E78','Eap','Eag']
election_combos = ['E1','E2','E3','E4','E5','E6','E78','Eap','Eag']
v_combos = ['_nVotesPct', '_nVotesPctInHH']
vs = [j+i for i in v_combos for j in election_combos]
f = ['nVotersInHH','nPAVInHH','nAffInHH','nDEMInHH','nREPInHH','nNPPInH
H',
      'mixedAfflsInHH','allAffInHH','uniformAffInHH']
df = clean_df(voters.loc[:,vs + f], f, vs)
```

```
In [26]: plt.rcParams["figure.figsize"] = (20,10)
# 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 [27]:
```
df.corr()
```

Out[27]:

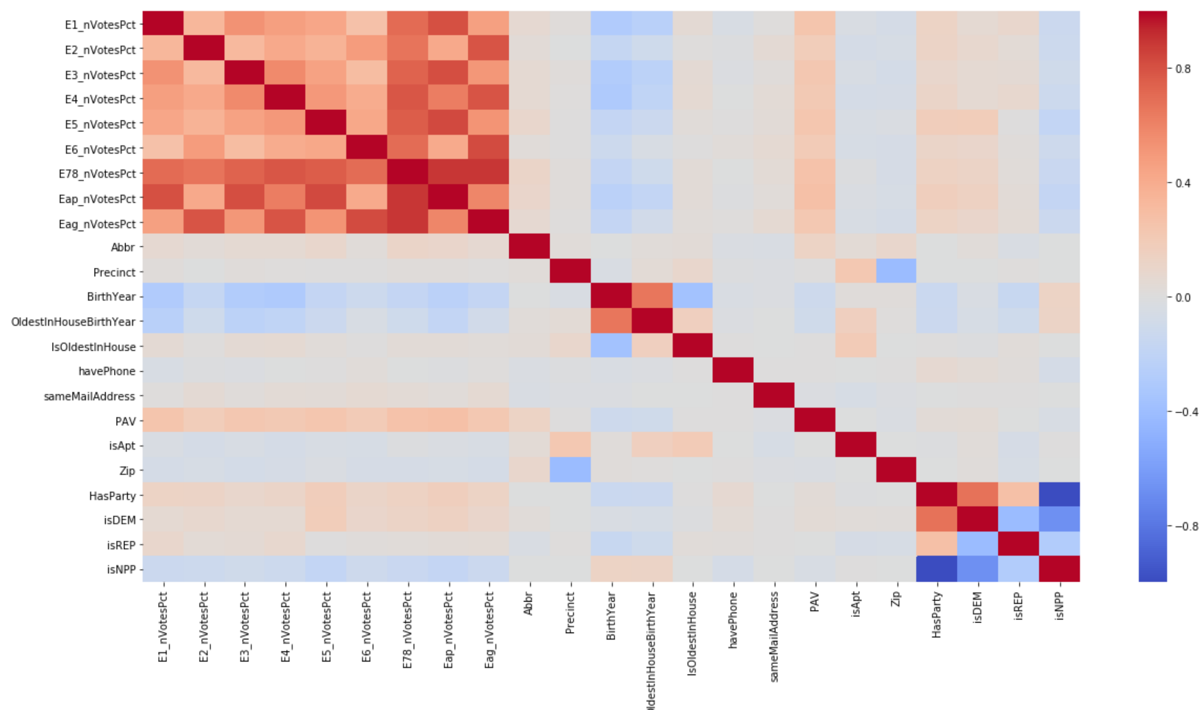
	E1_nVotesPct	E2_nVotesPct	E3_nVotesPct	E4_nVotesPct	E5_nVot
E1_nVotesPct	1.000000	0.339831	0.537430	0.475543	0.43714
E2_nVotesPct	0.339831	1.000000	0.324868	0.420487	0.36296
E3_nVotesPct	0.537430	0.324868	1.000000	0.572263	0.46211
E4_nVotesPct	0.475543	0.420487	0.572263	1.000000	0.50162
E5_nVotesPct	0.437146	0.362968	0.462117	0.501627	1.00000
E6_nVotesPct	0.273931	0.490110	0.305523	0.401027	0.42990
E78_nVotesPct	0.705537	0.671296	0.739326	0.788914	0.762721
Eap_nVotesPct	0.807519	0.420452	0.818999	0.629508	0.83099
Eag_nVotesPct	0.462675	0.794646	0.514796	0.794438	0.52752
E1_nVotesPctInHH	0.900745	0.294218	0.509467	0.427238	0.39535
E2_nVotesPctInHH	0.318438	0.849943	0.308094	0.381045	0.33567
E3_nVotesPctInHH	0.513558	0.293739	0.899706	0.522362	0.42651
E4_nVotesPctInHH	0.449724	0.376611	0.539791	0.875657	0.45452
E5_nVotesPctInHH	0.423193	0.333620	0.446190	0.462389	0.877612
E6_nVotesPctInHH	0.259877	0.428783	0.290281	0.368657	0.405941
E78_nVotesPctInHH	0.643507	0.570010	0.679586	0.698835	0.68479
Eap_nVotesPctInHH	0.731410	0.374770	0.746818	0.573125	0.73576
Eag_nVotesPctInHH	0.430802	0.670164	0.484132	0.702080	0.49719
nVotersInHH	-0.018642	0.006271	-0.023008	-0.016531	-0.02951
nPAVInHH	0.145686	0.104241	0.152138	0.136145	0.13795
nAffInHH	0.060136	0.064903	0.033656	0.045811	0.07408
nDEMInHH	0.028491	0.052513	0.034040	0.024275	0.10386
nREPInHH	0.086615	0.045301	0.029072	0.064564	-0.02197
nNPPInHH	-0.132718	-0.097441	-0.095469	-0.104779	-0.17195
mixedAffIsInHH	-0.022527	-0.029492	-0.031895	-0.019106	-0.04252
allAffInHH	0.154937	0.112031	0.124410	0.129214	0.18233
uniformAffInHH	0.083171	0.052582	0.076788	0.067726	0.08190

27 rows × 27 columns

Full Correlation Matrix of Voter characteristics

In [28]:
```
#election_combos = ['E1','E2','E3','E4','E5','E6','E12','E14', 'E16', 'E
34','E56','E78','Eap','Eag']
election_combos = ['E1','E2','E3','E4','E5','E6','E78','Eap','Eag']
v_combos = ['_nVotesPct']
vs = [j+i for i in v_combos for j in election_combos]
f = ['Abbr','Precinct','BirthYear','OldestInHouseBirthYear','IsOldestInH
ouse',
     'havePhone','sameMailAddress','PAV','isApt','Zip','HasParty', 'isDE
M','isREP','isNPP']
df = clean_df(voters.loc[:,vs + f], f, vs)
# converting PAV Y/N to True/False
df['PAV'] = df['PAV'].str.contains('Y')
```

In [29]:
```
plt.rcParams["figure.figsize"] = (20,10)
# 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, being the oldest in your household and age (negative birthYear), also with having a party affiliation and negatively with being a No Party Preference.

In [30]:
```
df.corr()
```

Out[30]:

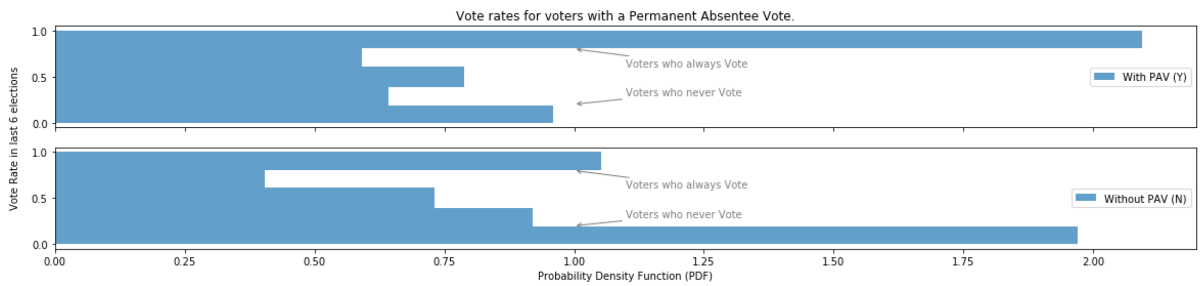
	E1_nVotesPct	E2_nVotesPct	E3_nVotesPct	E4_nVotesPct	E5_n
E1_nVotesPct	1.000000	0.339831	0.537430	0.475543	0.43
E2_nVotesPct	0.339831	1.000000	0.324868	0.420487	0.36
E3_nVotesPct	0.537430	0.324868	1.000000	0.572263	0.46
E4_nVotesPct	0.475543	0.420487	0.572263	1.000000	0.50
E5_nVotesPct	0.437146	0.362968	0.462117	0.501627	1.00
E6_nVotesPct	0.273931	0.490110	0.305523	0.401027	0.42
E78_nVotesPct	0.705537	0.671296	0.739326	0.788914	0.76
Eap_nVotesPct	0.807519	0.420452	0.818999	0.629508	0.83
Eag_nVotesPct	0.462675	0.794646	0.514796	0.794438	0.52
Abbr	0.070468	0.040450	0.060521	0.063047	0.08
Precinct	0.019923	0.000530	0.018823	0.012031	0.00
BirthYear	-0.293240	-0.168582	-0.282838	-0.294735	-0.17
OldestInHouseBirthYear	-0.245971	-0.101488	-0.217138	-0.195978	-0.12
IsOldestInHouse	0.051898	0.013839	0.054440	0.060815	0.02
havePhone	-0.041056	-0.005537	-0.019639	-0.002112	0.00
sameMailAddress	0.014139	0.052014	0.020852	0.042002	0.04
PAV	0.246619	0.182718	0.235247	0.219345	0.24
isApt	-0.034646	-0.066108	-0.041901	-0.062222	-0.03
Zip	-0.060122	-0.048985	-0.070626	-0.057127	-0.02
HasParty	0.127421	0.120025	0.094674	0.118015	0.18
isDEM	0.061561	0.087239	0.063763	0.062815	0.18
isREP	0.090061	0.042514	0.052849	0.081539	0.00
isNPP	-0.128936	-0.120706	-0.094969	-0.119068	-0.18

23 rows × 23 columns

PAV voters

In [31]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['PAV']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

In [32]:
```
# Summarize data
(k1, d1), (k0, d0) = df_g.groupby(['PAV'])
df_w = pd.DataFrame({k0:d0[vs[0]],k1:d1[vs[0]]})
title = 'Vote rates for voters with a Permanent Absentee Vote.'
df = show_vote_rate_and_summary(df_w, ['With PAV ('+k0+')','Without PAV
 ('+k1+')'], title)
```

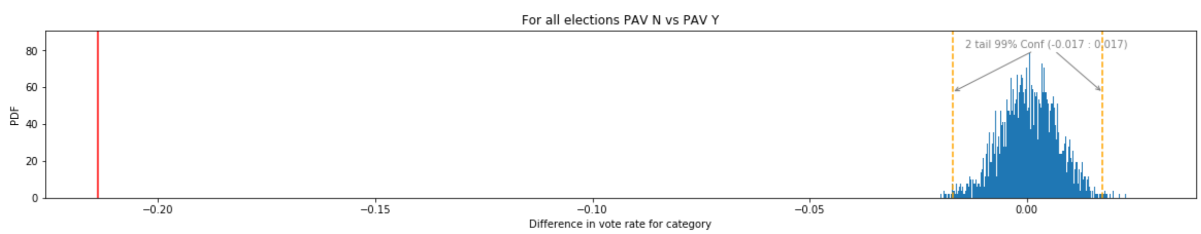


	Number of Voters		Voters as a %	
	With PAV (Y)	**Without PAV (N)**	**With PAV (Y)_pct**	**Without PAV (N)_pct**
Always	3141	895	39.8	20.0
Over Half	934	362	11.8	8.1
Half	1371	720	17.4	16.1
Under Half	1014	825	12.8	18.4
Never	1439	1677	18.2	37.4
Totals	7899	4479	100.0	100.0

In [33]:

```
# Run Stats
(kx,dx),(ky,dy) = df_s.groupby(['PAV'])
fig, axes = plt.subplots(figsize=(20,3))

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all elections
 PAV {} vs PAV {}'.format(kx,ky), tail=2)
df.loc['All elections PAV '+kx+':'+ky,outcols] = [sx,nx,rx,sy,ny,ry,emp_
diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	calc
All elections PAV N:Y	8261	22460	36.7809	22440	38570	58.1799	-21.399	-50.9905	0



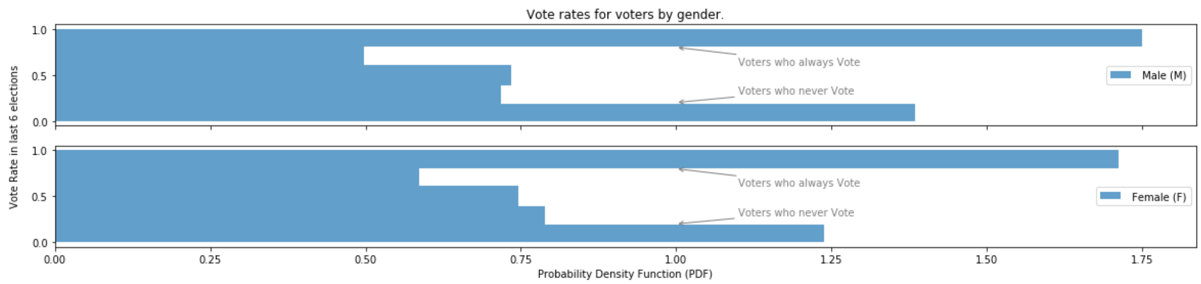
The low P value indicates we have to reject the null hypothesis and concludes with 99% confidence that having a permanent Absentee Ballot significantly increases the likelihood of your being in the always voter category. Our observations indicate ~20% greater chance of being an always voter.

Gender

In [34]:

```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['Gender']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

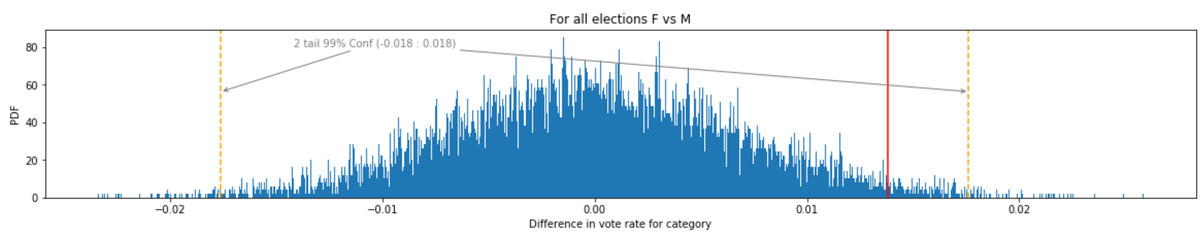
In [35]:
```
# Summarize data
(k2, d2),(k1, d1),(_, _) = df_g.groupby(['Gender'])
df_w = pd.DataFrame({k1:d1[vs[0]],k2:d2[vs[0]]})
title = 'Vote rates for voters by gender.'
df = show_vote_rate_and_summary(df_w, [' Male ('+k1+')',' Female ('+k2+
')'], title)
```



	Number of Voters		Voters as a %	
	Male (M)	Female (F)	Male (M)_pct	Female (F)_pct
Always	1751	1838	33.2	32.5
Over Half	524	663	9.9	11.7
Half	851	928	16.2	16.4
Under Half	757	892	14.4	15.8
Never	1386	1330	26.3	23.5
Totals	5269	5651	100.0	99.9

In [36]:
```
# Run Stats
(kx, dx),(ky, dy),(_, _) = df_s.groupby(['Gender'])
fig, axes = plt.subplots(figsize=(20,3))

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all elections
{} vs {}'.format(kx,ky), tail=2)
df.loc['All elections Gender'+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,e
mp_diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	ca
All elections GenderF:M	14797	28760	51.4499	13243	26449	50.0699	1.37998	3.24006	0.(



Running our two Statistical Significance tests indicates that fail to reject the null hypothesis and can say with 99% confidence that the variation in male and female vote rate we see is likely due to chance. Note I'm putting more weight on the permutation test result as it is more appropriate given our sampling method.

It is interesting to observe that on an individual level men are more likely to be a member of one of the extreme categories (ie always voting or never voting), women are more likely to sometimes cast their ballot.

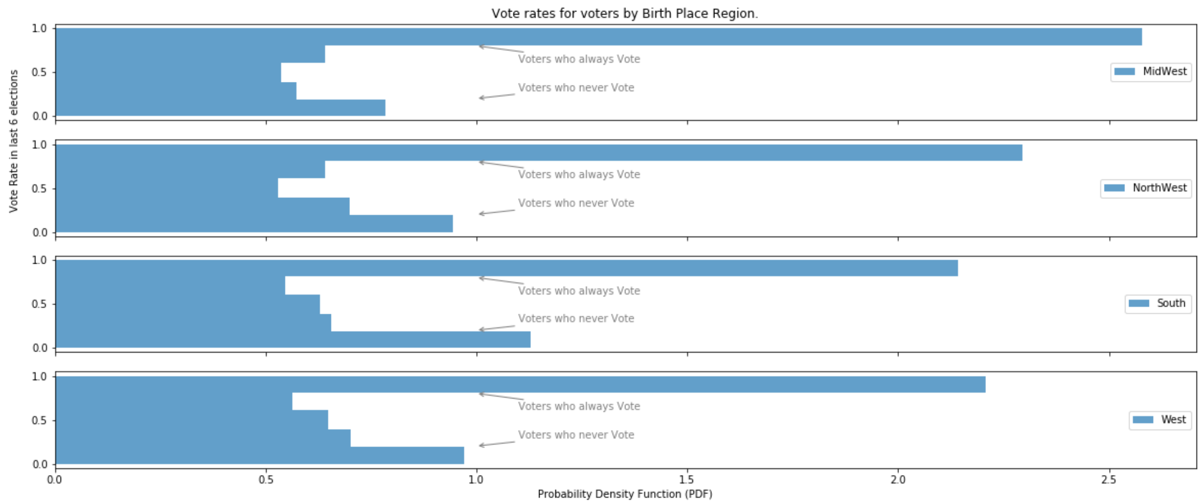
BirthState Region

Excluding Californians

In [37]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['BirthPlaceState'
,'BirthPlaceStateRegion']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

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

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

In [38]:

```
# Summarize data
(k3, d3), (k2, d2), (k1, d1), (k0, d0) = df_g.groupby(['BirthPlaceStateRegion'])
df_w = pd.DataFrame({k3:d3[vs[0]], k2:d2[vs[0]], k1:d1[vs[0]], k0:d0[vs[0]]})
title = 'Vote rates for voters by Birth Place Region.'
df = show_vote_rate_and_summary(df_w, [k3,k2,k1,k0], title)
```

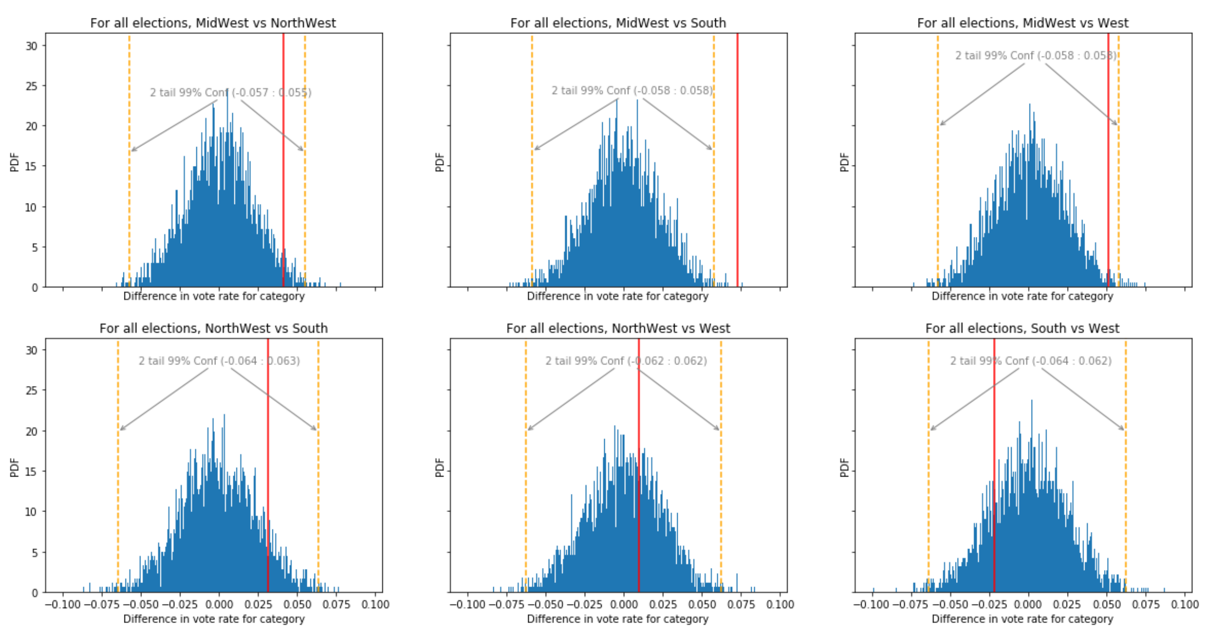


	Number of Voters				Voters as a %			
	MidWest	NorthWest	South	West	MidWest_pct	NorthWest_pct	South_pct	Wes
Always	286	187	171	182	49.0	43.6	40.7	41.9
Over Half	75	55	46	49	12.8	12.8	11.0	11.3
Half	69	50	58	62	11.8	11.7	13.8	14.3
Under Half	67	60	55	61	11.5	14.0	13.1	14.1
Never	87	77	90	80	14.9	17.9	21.4	18.4
Totals	584	429	420	434	100.0	100.0	100.0	100.

In [39]:

```
# Run Stats
g3, g2, g1, g0  = df_s.groupby(['BirthPlaceStateRegion'])
region_combos = list(itertools.combinations([g3, g2, g1, g0], 2))
layout = [(i,j) for i in range(2) for j in range(3)]

fig, axes = plt.subplots(2,3,figsize=(20,10), sharex=True, sharey=True)

df = pd.DataFrame(columns=outcols)
for ((kx,dx),(ky,dy)),loc in zip(region_combos,layout):
    #display(Markdown('Processing **{} & {}**...'.format(kx, ky)))
    sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
    cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-s
ided')
    pp, emp_diff, axes[loc] = two_sample_perm_test_diff_frac_votes(dx,dy
,axes[loc],
                                                                    'all e
lections, {} vs {}'.format(kx,ky), tail=2)
    df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,em
p_diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	ca
All elections: MidWest:NorthWest	2054	3163	64.9383	1377	2265	60.7947	4.14365	3.1
All elections: MidWest:South	2054	3163	64.9383	1317	2285	57.6368	7.30159	5.4
All elections: MidWest:West	2054	3163	64.9383	1386	2317	59.8187	5.11962	3.8
All elections: NorthWest:South	1377	2265	60.7947	1317	2285	57.6368	3.15794	2.1
All elections: NorthWest:West	1377	2265	60.7947	1386	2317	59.8187	0.975971	0.6
All elections: South:West	1317	2285	57.6368	1386	2317	59.8187	-2.18197	-1.



People born in the MidWest states tend to vote more often than those born elsewhere in the USA out of CA, grouped by birth region. The statistical analysis causes us to reject the null hypothesis (that voters born in these regions have the same vote rate) in just one case although it came close in a few others:

- Voters born in the MidWest are more likely to vote than those born in the South (obs $\approx 7\%$)

We fail to reject the null hypothesis when comparing vote rates for all other combinations of regions - the variations in vote rate we see in our data is 99% confident to be due to chance.

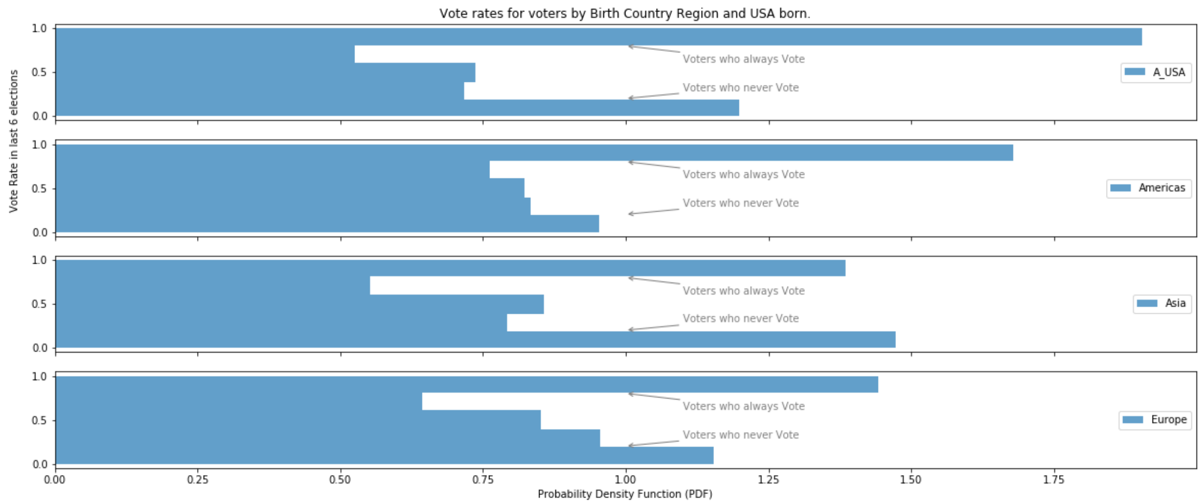
BirthCountry

In [40]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['BirthPlaceCountr
yRegion']
df_w = clean_df(voters.loc[:,vs + f], f, vs)
display(df_w.BirthPlaceCountryRegion.value_counts())

# removing Oceania and Africa as sample size is too small
df_w['BirthPlaceCountryRegion'].replace('Africa', np.NaN, inplace=True)
df_w['BirthPlaceCountryRegion'].replace('Oceania', np.NaN, inplace=True)
df_w['BirthPlaceCountryRegion'].replace('USA', 'A_USA', inplace=True)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

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

In [41]:

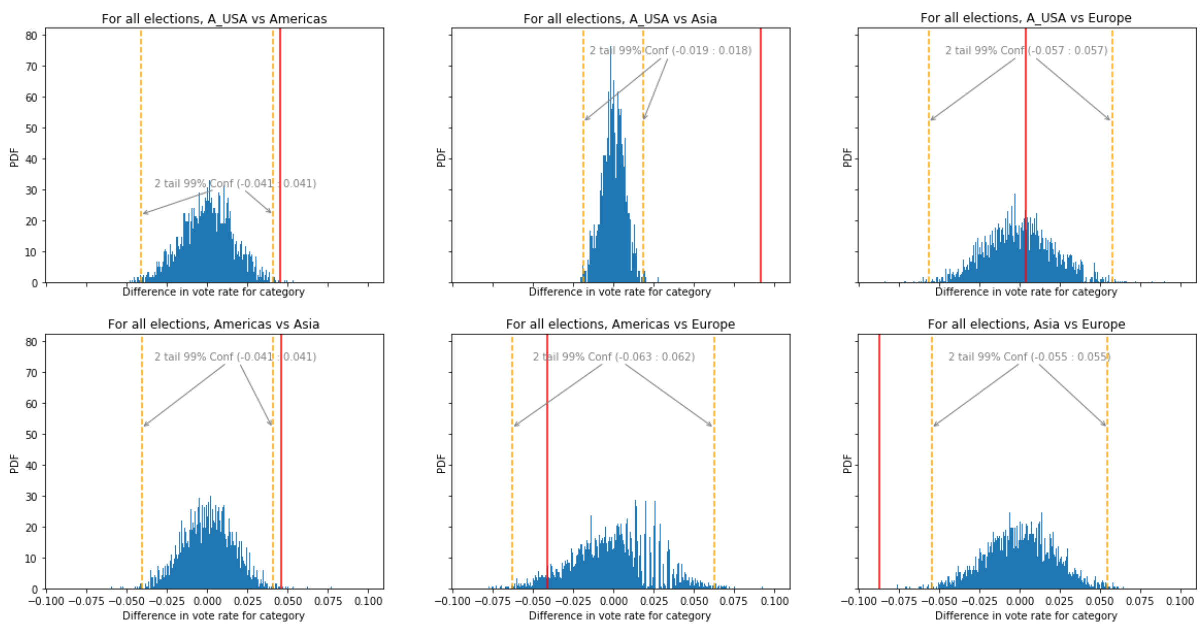
```
# Summarize data
(k3, d3), (k2, d2), (k1, d1), (k0, d0) = df_g.groupby(['BirthPlaceCountr
yRegion'])
df_w = pd.DataFrame({k3:d3[vs[0]], k0:d0[vs[0]], k1:d1[vs[0]], k2:d2[vs[
0]]})
title = 'Vote rates for voters by Birth Country Region and USA born.'
df = show_vote_rate_and_summary(df_w, [k3,k2,k1,k0], title)
```



	Number of Voters				Voters as a %			
	A_USA	Americas	Asia	Europe	A_USA_pct	Americas_pct	Asia_pct	Europe_pc
Always	2438	88	951	145	36.2	31.9	26.3	27.4
Over Half	708	42	399	68	10.5	15.2	11.0	12.9
Half	1092	50	681	99	16.2	18.1	18.8	18.7
Under Half	967	46	573	101	14.3	16.7	15.9	19.1
Never	1536	50	1011	116	22.8	18.1	28.0	21.9
Totals	6741	276	3615	529	100.0	100.0	100.0	100.0

In [42]:
```
# Run Stats
g3, g2, g1, g0  = df_s.groupby(['BirthPlaceCountryRegion'])
region_combos = list(itertools.combinations([g3, g2, g1, g0], 2))
layout = [(i,j) for i in range(2) for j in range(3)]

fig, axes = plt.subplots(2,3,figsize=(20,10), sharex=True, sharey=True)

df = pd.DataFrame(columns=outcols)
for ((kx,dx),(ky,dy)),loc in zip(region_combos,layout):
    #display(Markdown('Processing **{} & {}**...'.format(kx, ky)))
    sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
    cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-s
ided')
    pp, emp_diff, axes[loc] = two_sample_perm_test_diff_frac_votes(dx,dy
,axes[loc],
                                                                   'all e
lections, {} vs {}'.format(kx,ky), tail=2)
    df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,em
p_diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_
All elections: A_USA:Americas	18449	34199	53.946	1349	2730	49.4139	4.5321	4.569
All elections: A_USA:Asia	18449	34199	53.946	7877	17586	44.7913	9.15471	19.73
All elections: A_USA:Europe	18449	34199	53.946	794	1483	53.5401	0.4059	0.307
All elections: Americas:Asia	1349	2730	49.4139	7877	17586	44.7913	4.62261	4.513
All elections: Americas:Europe	1349	2730	49.4139	794	1483	53.5401	-4.1262	-2.55
All elections: Asia:Europe	7877	17586	44.7913	794	1483	53.5401	-8.74881	-6.49



The difference if vote rate based on the world region a voter was born in was statistically significant in 4 of our 6 comparison pairs:

- voters born in the USA are more likely to vote than those born in Asia (obs: $\approx 9.2\%$) SS 99%
- voters born in Europe are more likely to vote than those born in Asia (obs: $\approx 6.5\%$) SS 99%
- voters born in the USA are more likely to vote than those born elsewhere in the Americas (obs: $\approx 4.5\%$) just SS 99%
- voters born elsewhere in the Americas are more likely to vote than those born in Asia (obs: $\approx 4.6\%$) just SS 99%

We fail to reject the null hypothesis when comparing vote rate of people born in the USA to those born in Europe and when comparing vote rate for people born elsewhere in the Americas with to those born in Europe, our observed difference in vote rate is likely due to chance. The sample sizes were small in some of these cases and the results only just statistically significance so you may not wish to take action on these results.

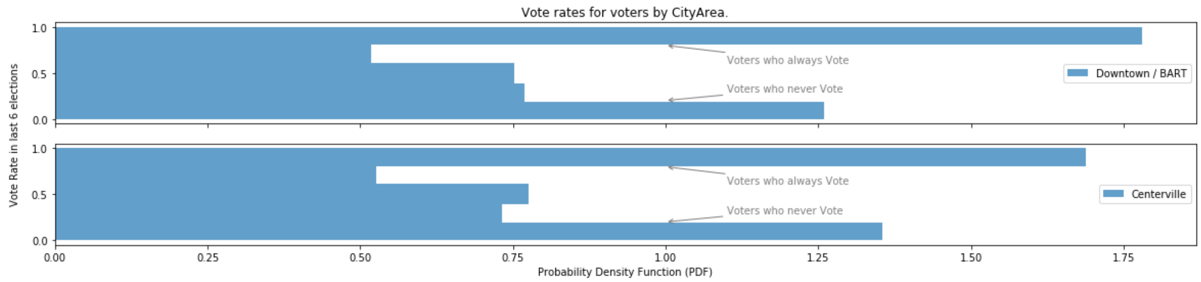
Voters born in Asia are more likely to end up in the never vote category. USA born voters are more likely to be in the Always vote category.

CityArea

In [43]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['CityArea']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

print('Removing {} cityarea as our data only has {} voters in that area'
.format(
df_w.CityArea.value_counts().index[-1],df_w.CityArea.value_counts()[-1
]))
df_w['CityArea'].replace('Niles', np.NaN, inplace=True)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

```
Removing Niles cityarea as our data only has 3 voters in that area
```

In [44]:
```
# Summarize data
(k1, d1),(k0, d0) = df_g.groupby(['CityArea'])
df_w = pd.DataFrame({k0:d0[vs[0]],k1:d1[vs[0]]})
title = 'Vote rates for voters by CityArea.'
df = show_vote_rate_and_summary(df_w, [k0,k1], title)
```

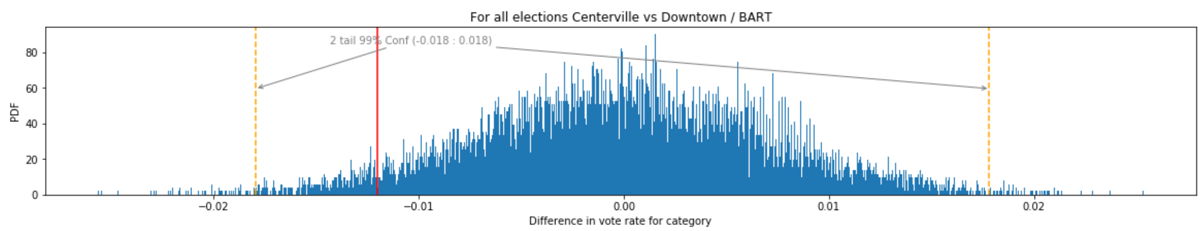


	Number of Voters		Voters as a %	
	Downtown / BART	**Centerville**	**Downtown / BART_pct**	**Centerville_pct**
Always	1272	2762	33.8	32.1
Over Half	390	906	10.4	10.5
Half	622	1468	16.5	17.0
Under Half	579	1260	15.4	14.6
Never	900	2216	23.9	25.7
Totals	3763	8612	100.0	99.9

In [45]:

```
# Run Stats
(kx, dx),(ky, dy) = df_s.groupby(['CityArea'])
fig, axes = plt.subplots(figsize=(20,3))

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all elections
{} vs {}'.format(kx,ky), tail=2)
df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,emp_di
ff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	c
All elections: Centerville:Downtown / BART	21284	42624	49.9343	9403	18388	51.1366	-1.2023	-



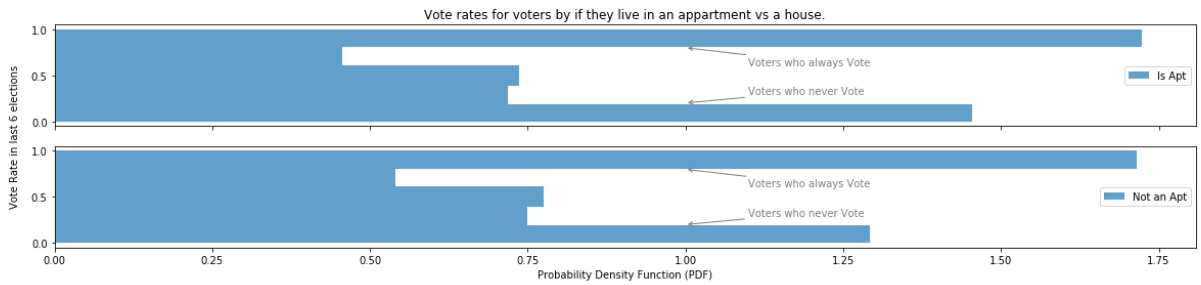
Voters in Downtown/BART are a little more likely to vote than those in Centerville this affect carries over to them also being more likely to be in the always vote category and less like to be in the never vote category. However this affect is small observed at $\approx 1.2\%$ and is not statistically significant at 99% confidence its could be caused by chance.

Living in an Apartment

In [46]:

```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['isApt']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

In [47]:
```
# Summarize data
(k1, d1),(k0, d0) = df_g.groupby(['isApt'])
df_w = pd.DataFrame({k0:d0[vs[0]],k1:d1[vs[0]]})
title = 'Vote rates for voters by if they live in an appartment vs a hou
se.'
df = show_vote_rate_and_summary(df_w, ['Is Apt','Not an Apt'], title)
```

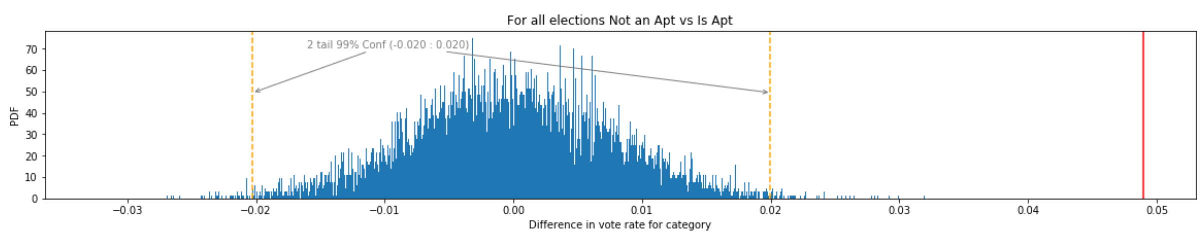


	Number of Voters		Voters as a %	
	Is Apt	**Not an Apt**	**Is Apt_pct**	**Not an Apt_pct**
Always	809	3227	32.7	32.6
Over Half	225	1071	9.1	10.8
Half	400	1691	16.2	17.1
Under Half	355	1484	14.4	15.0
Never	683	2433	27.6	24.6
Totals	2472	9906	100.0	100.1

In [48]:

```python
# Run Stats
(kx, dx),(ky, dy) = df_s.groupby(['isApt'])
fig, axes = plt.subplots(figsize=(20,3))
kx = 'Is Apt' if kx else 'Not an Apt'
ky = 'Is Apt' if kx else 'Not an Apt'

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-sided')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all elections {} vs {}'.format(kx,ky), tail=2)
df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,emp_diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	calc_
All elections: Not an Apt:Is Apt	25635	50085	51.183	5066	10945	46.286	4.89701	9.28238	1.657 20



Voters who live in apartments are less likely to vote than voters who's address does not include an apartment number (obs: $\approx 4.9\%$). This is a statistically significant result at 99% confidence.

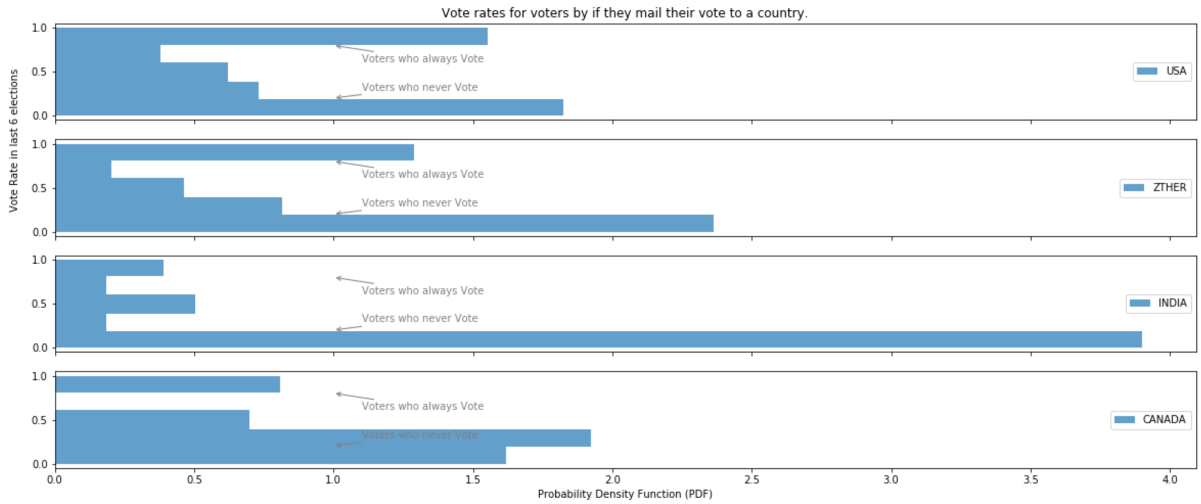
It is interesting to notice that voters living in Apartments seem a little more likely to be in the never voter category although are members of the always vote category about as frequently as other voters.

Exploring how MailCountry is related to voting behavior

In [49]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['MailCountry']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

for_other=['GERMANY', 'JAPAN', 'THAILAND', 'ISRAEL', 'PHILIPPINES', 'CHI
NA', 'MYANMAR',
            'HONG KONG','TAIWAN', 'AUSTRALIA', 'SERBIA', 'SINGAPORE', 'SP
AIN','GHANA',
            'COSTA RICA', 'AUSTRIA', 'CHILE', 'LEBANON','GREECE', 'UNITED
 KINGDOM', 'MEXICO',
            'NEW ZEALAND','PAKISTAN', 'PERU', 'SWITZERLAND', 'ARGENTINA']
df_w['MC_Main'] = df_w.loc[df_w.MailCountry.notnull(),'MailCountry'].ast
ype(str)
df_w.loc[df_w.MC_Main.isin(for_other) == True,['MC_Main']] = 'ZTHER'
df_w = df_w.drop('MailCountry', axis=1)

f = ['MC_Main']

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

In [50]:

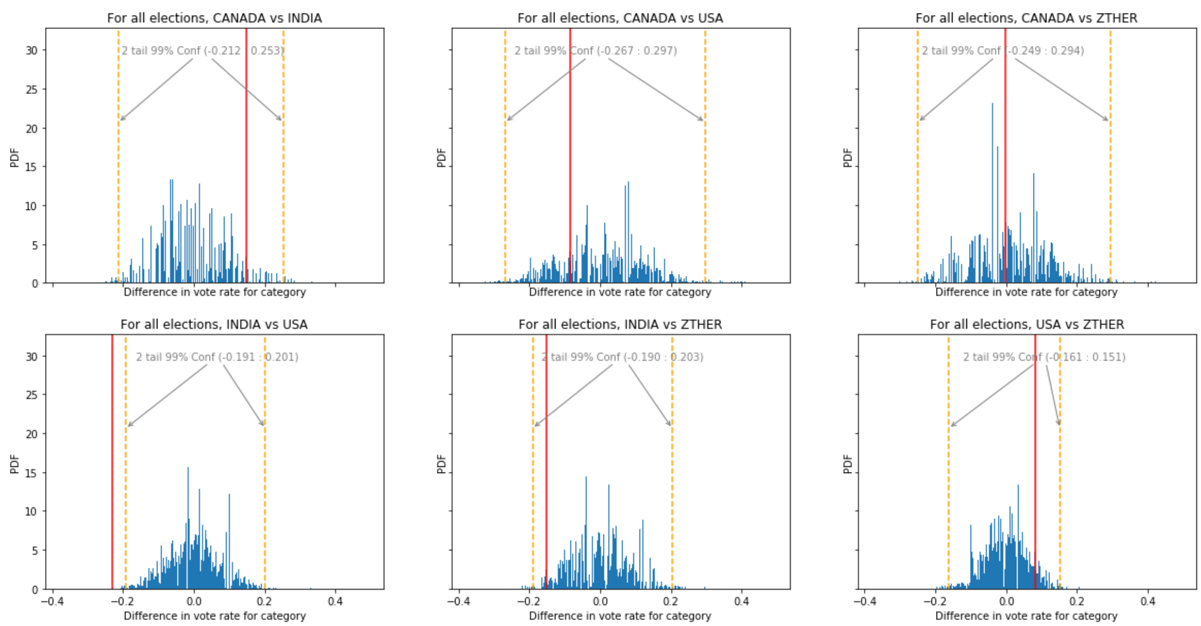
```
# Summarize data
(k3, d3), (k2, d2), (k1, d1), (k0, d0) = df_g.groupby(['MC_Main'])
df_w = pd.DataFrame({k1:d1[vs[0]],k0:d0[vs[0]],k2:d2[vs[0]],k3:d3[vs[0
]]})
title = 'Vote rates for voters by if they mail their vote to a country.'
df = show_vote_rate_and_summary(df_w, [k1,k0,k2,k3], title)
```



	Number of Voters				Voters as a %			
	USA	ZTHER	INDIA	CANADA	USA_pct	ZTHER_pct	INDIA_pct	CANADA_pct
Always	97	12	2	2	29.5	24.5	7.4	15.4
Over Half	25	2	1	0	7.6	4.1	3.7	0.0
Half	45	5	3	2	13.7	10.2	11.1	15.4
Under Half	48	8	1	5	14.6	16.3	3.7	38.5
Never	114	22	20	4	34.7	44.9	74.1	30.8
Totals	329	49	27	13	100.1	100.0	100.0	100.1

In [51]:
```
# Run Stats
g3, g2, g1, g0  = df_s.groupby(['MC_Main'])
region_combos = list(itertools.combinations([g3, g2, g1, g0], 2))
layout = [(i,j) for i in range(2) for j in range(3)]

fig, axes = plt.subplots(2,3,figsize=(20,10), sharex=True, sharey=True)

df = pd.DataFrame(columns=outcols)
for ((kx,dx),(ky,dy)),loc in zip(region_combos,layout):
    #display(Markdown('Processing **{} & {}**...'.format(kx, ky)))
    sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
    cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-s
ided')
    pp, emp_diff, axes[loc] = two_sample_perm_test_diff_frac_votes(dx,dy
,axes[loc],
                                                                      'all e
lections, {} vs {}'.format(kx,ky), tail=2)
    df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,em
p_diff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_
All elections: CANADA:INDIA	21	60	35	28	138	20.2899	14.7101	2.204
All elections: CANADA:USA	21	60	35	662	1524	43.4383	-8.43832	-1.29
All elections: CANADA:ZTHER	21	60	35	77	218	35.3211	-0.321101	-0.04
All elections: INDIA:USA	28	138	20.2899	662	1524	43.4383	-23.1485	-5.28
All elections: INDIA:ZTHER	28	138	20.2899	77	218	35.3211	-15.0312	-3.03
All elections: USA:ZTHER	662	1524	43.4383	77	218	35.3211	8.11722	2.268



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 $\approx 70\%$ chance of being a never voter!

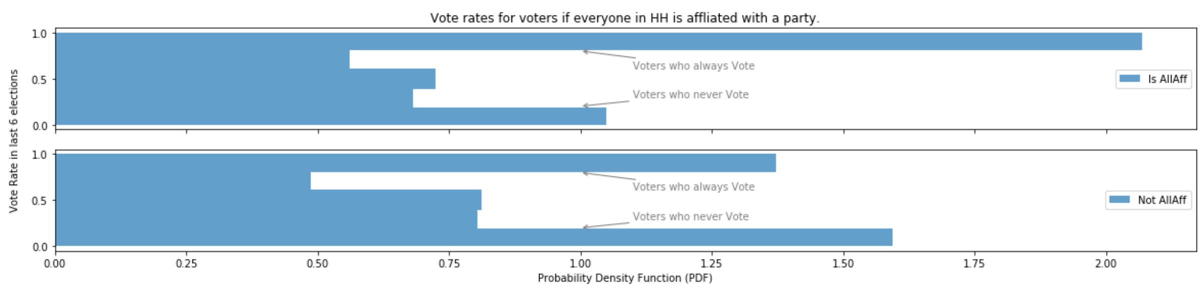
That said there was little statistical significance in these findings as the sample sizes are so low. Only in one pairs of tests did we meet the 99% confidence level to reject the null hypothesis and say that voters with a mailing country of India are less likely to vote than those with a mail country of USA.

Exploring how voter's household make up reflects in voting behavior

First looking at is all Voters in the Household are affiliated with a party:

In [52]:
```
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['allAffInHH']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

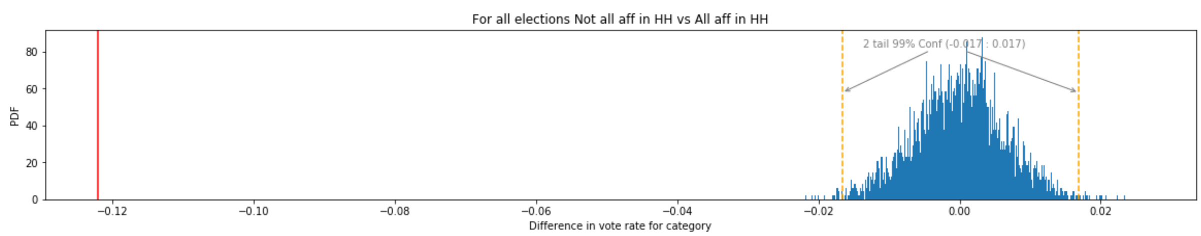
In [53]:
```
# Summarize data
(k1, d1),(k0, d0) = df_g.groupby(['allAffInHH'])
df_w = pd.DataFrame({k0:d0[vs[0]],k1:d1[vs[0]]})
title = 'Vote rates for voters if everyone in HH is affliated with a par
ty.'
df = show_vote_rate_and_summary(df_w, ['Is AllAff','Not AllAff'], title)
```



	Number of Voters		Voters as a %	
	Is AllAff	**Not AllAff**	**Is AllAff_pct**	**Not AllAff_pct**
Always	2403	1633	39.3	26.1
Over Half	687	609	11.2	9.7
Half	974	1117	15.9	17.8
Under Half	833	1006	13.6	16.1
Never	1220	1896	19.9	30.3
Totals	6117	6261	99.9	100.0

In [54]:
```
# Run Stats
(kx, dx),(ky, dy) = df_s.groupby(['allAffInHH'])
fig, axes = plt.subplots(figsize=(20,3))
kx = 'All aff in HH' if kx else 'Not all aff in HH'
ky = 'All aff in HH' if kx else 'Not all aff in HH'

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                              'all elections
{} vs {}'.format(kx,ky), tail=2)
df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,emp_di
ff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	cal
All elections: Not all aff in HH:All aff in HH	13289	30122	44.1173	17412	30908	56.3349	-12.2177	-30.1809	4.2 20(

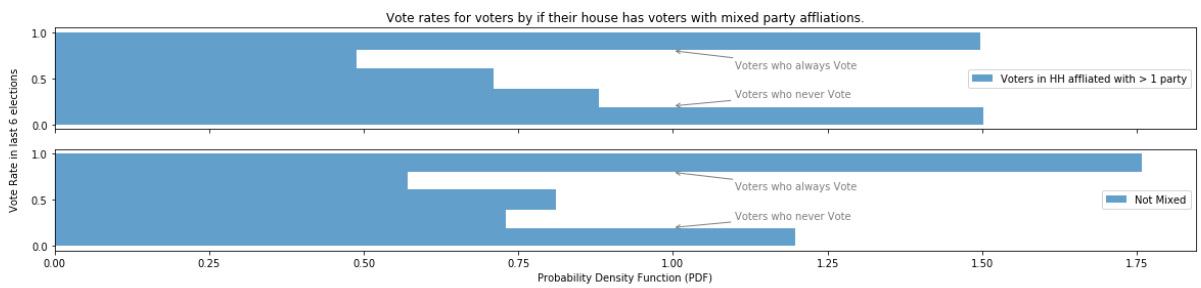


If everyone in your house hold is affiliated with a political party you are 12% more likely to vote than if you don't live in such a household. This result was statistically significant at 99% confidence. This included single voter households.

Then looking at if the voters who live in a house with more than one voter and the household voters are affiliated with more than one party between them.

In [55]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['mixedAfflsInHH',
'nVotersInHH']
df_w = clean_df(voters.loc[:,vs + f], f, vs)
#removing housholds with less than one voter
df_w = df_w.loc[df_w.nVotersInHH>1]
df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

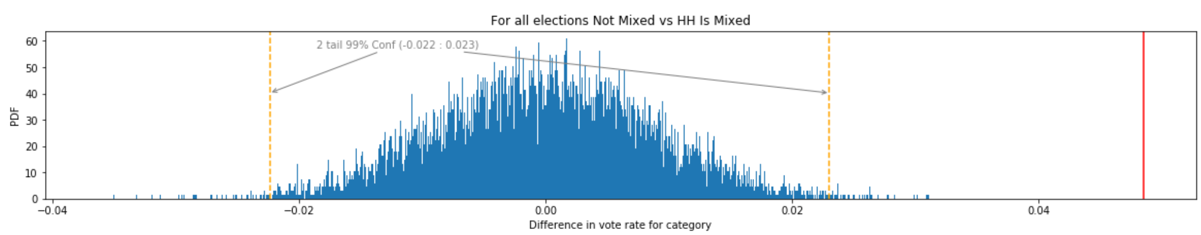
In [56]:
```
# Summarize data
(k1, d1),(k0, d0) = df_g.groupby(['mixedAfflsInHH'])
df_w = pd.DataFrame({k0:d0[vs[0]],k1:d1[vs[0]]})
title = 'Vote rates for voters by if their house has voters with mixed p
arty affliations.'
df = show_vote_rate_and_summary(df_w, ['Voters in HH affliated with > 1
 party','Not Mixed'], title)
```



	Number of Voters		Voters as a %	
	Voters in HH affliated with > 1 party	**Not Mixed**	**Voters in HH affliated with > 1 party_pct**	**Not Mixed_pct**
Always	585	2534	28.5	33.4
Over Half	201	867	9.8	11.4
Half	321	1353	15.6	17.8
Under Half	362	1108	17.6	14.6
Never	587	1726	28.6	22.7
Totals	2056	7588	100.1	99.9

In [57]:
```
# Run Stats
(kx, dx),(ky, dy) = df_s.groupby(['mixedAfflsInHH'])
fig, axes = plt.subplots(figsize=(20,3))

kx = 'HH Is Mixed' if kx else 'Not Mixed'
ky = 'HH Is Mixed' if kx else 'Not Mixed'

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all elections
{} vs {}'.format(kx,ky), tail=2)
df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,emp_di
ff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	calc
All elections: Not Mixed:HH Is Mixed	19510	37490	52.0405	5029	10657	47.1896	4.8509	8.83943	9.62 19

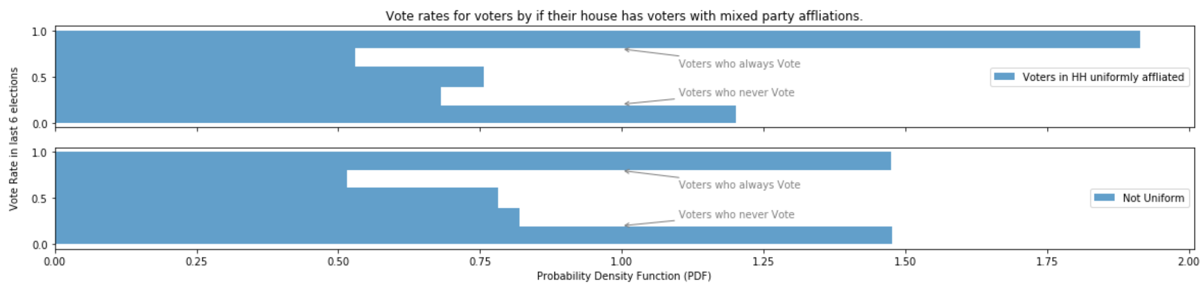


Living in a household with people who are affiliated with another party meant you were 4.9% (SS at 99%) less likely to vote than if you lived in a household where all the voters in the household were affiliated with the same party. (NPP voters did not count as affiliated and single voter households were removed from the analysis)

Then looking at if the voters are uniformly affiliated ie with the same party or all NPP. This measure includes single voter households which are all by default 'uniformly' affiliated.

In [58]:
```
# Gather data
e = 'E78'
vs, f = [e+'_nVotesPct', e+'_nVotesPos', e+'_nVotes'],['uniformAffInHH']
df_w = clean_df(voters.loc[:,vs + f], f, vs)

df_g, df_s = df_w.loc[:,[e+'_nVotesPct']+f], df_w.loc[:,[e+'_nVotesPos',
e+'_nVotes']+f]
```

In [59]:
```
# Summarize data
(k1, d1),(k0, d0) = df_g.groupby(['uniformAffInHH'])
df_w = pd.DataFrame({k0:d0[vs[0]],k1:d1[vs[0]]})
title = 'Vote rates for voters by if their house has voters with mixed p
arty affliations.'
df = show_vote_rate_and_summary(df_w, ['Voters in HH uniformly affliate
d','Not Uniform'], title)
```

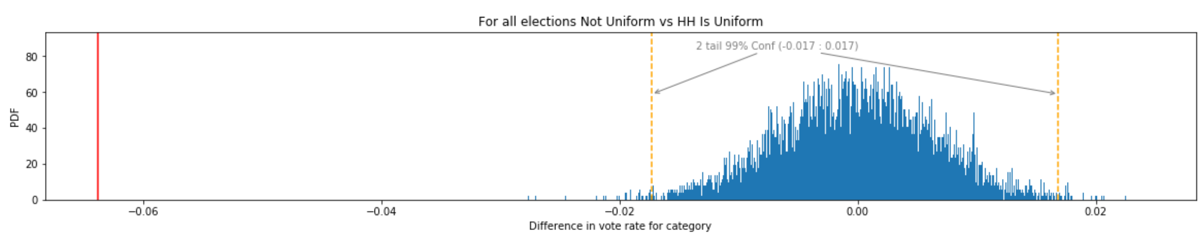


	Number of Voters		Voters as a %	
	Voters in HH uniformly affliated	**Not Uniform**	**Voters in HH uniformly affliated_pct**	**Not Uniform_pct**
Always	2477	1559	36.4	28.0
Over Half	722	574	10.6	10.3
Half	1133	958	16.6	17.2
Under Half	927	912	13.6	16.4
Never	1555	1561	22.8	28.1
Totals	6814	5564	100.0	100.0

In [60]:

```
# Run Stats
(kx, dx),(ky, dy) = df_s.groupby(['uniformAffInHH'])
fig, axes = plt.subplots(figsize=(20,3))

kx = 'HH Is Uniform' if kx else 'Not Uniform'
ky = 'HH Is Uniform' if kx else 'Not Uniform'

df = pd.DataFrame(columns=outcols)
sx,nx,rx,sy,ny,ry = get_two_sample_ns(dx, dy)
cz,cp = props.proportions_ztest([sx,sy], [nx,ny], alternative='two-side
d')
pp, emp_diff, axes = two_sample_perm_test_diff_frac_votes(dx,dy,axes,
                                                          'all elections
{} vs {}'.format(kx,ky), tail=2)
df.loc['All elections: '+kx+':'+ky, outcols] = [sx,nx,rx,sy,ny,ry,emp_di
ff*100,cz,cp,pp]

display(df)
plt.show()
```

	votes_s0	elec_n0	rate_r0	votes_s1	elec_n1	rate_r1	emp_diff	calc_z	c
All elections: Not Uniform:HH Is Uniform	13029	27822	46.8298	17672	33208	53.2161	-6.38625	-15.7155	1 5



Uniformly affliated households were 6.4% more likely to vote than households with a mix of voters.