EDA_n

August 1, 2025

[1]:
```python
# analytics
import pandas as pd
import numpy as np
import scipy.stats as stats
import statsmodels.formula.api as smf
#spatial
import osmnx as ox
import geopandas as gpd
import contextily as cx
# plotting
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.colors import LinearSegmentedColormap
#settings
import warnings
```

[2]:
```python
# suppress deprication warnings
warnings.filterwarnings('ignore')
# plot settings
sns.set_style('darkgrid')
sns.set_palette('rocket')

# erasmus colors
rgb_1 = (0,35,40) # eur bright green
rgb_2 = (12,128,102) # eur green
rgb_3 = (227, 218, 216) #eur warm grey
rgb_4 = (255,215,0) # ese yellow

hex_1 = '#0c8066'
hex_2 = '#002328'
hex_3 = '#e3dad8'
hex_4 = '#ffd700'
# normalize for sns and pd plotting
rgb_1, rgb_2, rgb_3, rgb_4 = [c/255 for c in rgb_1], [c/255 for c in rgb_2], [c/
↪255 for c in rgb_3], [c/255 for c in rgb_4]
# eur color palettes
```

```
yellow_bright = LinearSegmentedColormap.from_list(name='yellow_bright',colors=[hex_4, hex_3, hex_1])
yellow_dark = LinearSegmentedColormap.from_list(name='yellow_dark', colors=[hex_4, hex_3, hex_2])
bright_dark =  LinearSegmentedColormap.from_list(name='light_dark', colors=[hex_1, hex_3, hex_2])
sequential = LinearSegmentedColormap.from_list(name='sequential', colors=[hex_3, hex_1])
discrete = LinearSegmentedColormap.from_list(name='discrete', colors=[hex_1, hex_2, hex_3, hex_4])
```

[3]:

```
yellow_bright
```

[3]:

[4]:

```
yellow_dark
```

[4]:

[5]:

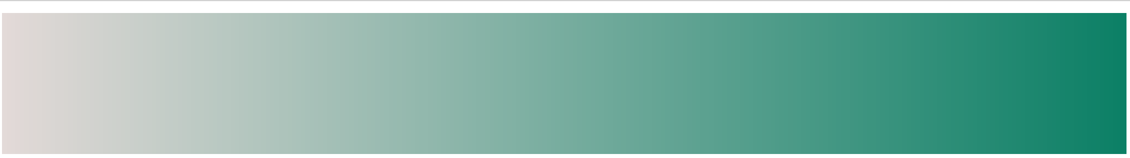
```
bright_dark
```

[5]:

[6]:

```
sequential
```

[6]:



[7]:
```
discrete
```

[7]:

[8]:
```
# load 2023 data set
path = '../data/2023/fema_national_household_survey_2023_data_and_codebook.xlsx'
df = pd.read_excel(path, sheet_name='Coastal Flooding', header=1)
```

0.1 Data Cleaning

Let's select the important variables, rename and recode

[9]:
```
variables =␣
 ↪['id','state','zipcode','geographic_division','census_region','county','cfld_iawareness','c
            ␣
 ↪'cfld_floodzone','cfld_prepactions_a','cfld_prepactions_b','cfld_prepactions_c','cfld_prepa
            ␣
 ↪'cfld_prepactions_e','cfld_prepactions_f','cfld_prepactions_g','cfld_prepactions_h','cfld_p
            ␣
 ↪'cfld_prepactions_j','cfld_prepactions_k','cfld_prepactions_l','cfld_prepactions_m','cfld_p
            ␣
 ↪'age','sex','education','race_selfid','homeownership','income','rentmortgage',␣
 ↪'rurality','hazard_weight']
df = df[variables]
```

[10]:
```
# Let's rename some variables
df = df.rename(columns= {
    'cfld_prepactions_a': 'supplies',
    'cfld_prepactions_b': 'insured',
    'cfld_prepactions_c': 'involved',
    'cfld_prepactions_d': 'learned_routes',
    'cfld_prepactions_e': 'made_plan',
    'cfld_prepactions_f': 'made_safer',
    'cfld_prepactions_g': 'planned_neighbors',
    'cfld_prepactions_h': 'practiced_drills',
    'cfld_prepactions_i': 'documents',
    'cfld_prepactions_j': 'rainy_day',
    'cfld_prepactions_k': 'alerts',
    'cfld_prepactions_l': 'family_communication',
    'cfld_prepactions_m': 'none',
    'cfld_prepactions_n': 'dont_know',
    'cfld_iawareness': 'awareness',
```

```
    'cfld_iperception': 'perception',
    'cfld_iexp': 'experience',
    'cfld_floodzone': 'floodzone',
    'race_selfid': 'race'
})
```

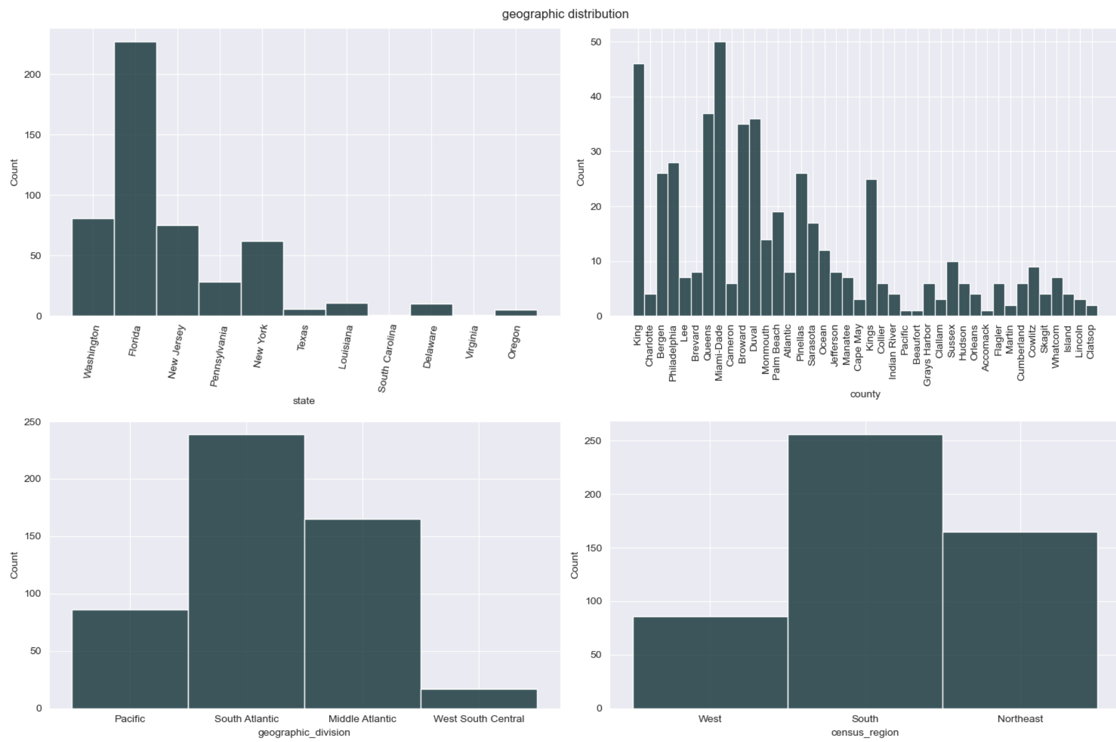
[11]:
```
df.head()
```

[11]:
```
   id         state  zipcode geographic_division census_region        county  \
0   1    Washington    98033             Pacific          West          King
1   2       Florida    33950      South Atlantic         South     Charlotte
2   3    New Jersey     7031     Middle Atlantic     Northeast        Bergen
3   4  Pennsylvania    19115     Middle Atlantic     Northeast  Philadelphia
4   5  Pennsylvania    19148     Middle Atlantic     Northeast  Philadelphia

  awareness perception experience floodzone  …   dont_know    age     sex  \
0        No        Yes         No        No  …       Blank  20-29    Male
1       Yes        Yes        Yes       Yes  …       Blank  50-59  Female
2        No        Yes        Yes        No  …       Blank  30-39  Female
3   Unknown    Unknown    Unknown        No  …  Don't know  40-49  Female
4        No        Yes        Yes        No  …       Blank  30-39    Male

                                          education   race homeownership  \
0                                 Bachelor's degree  White           Own
1  Post graduate work/degree or professional degree  White           Own
2                      High school degree or diploma  White          Rent
3                      High school degree or diploma  White          Rent
4                                 Bachelor's degree  White           Own

                income      rentmortgage rurality hazard_weight
0    $75,000 to $99,999   $1,001 - $1,500    Urban      0.255097
1  $150,000 to $199,999  More than $3,000    Urban      2.836145
2    $35,000 to $49,999   $1,001 - $1,500    Urban      1.165971
3    $50,000 to $74,999        Don't know    Urban      0.794098
4  $100,000 to $149,999   $1,001 - $1,500    Urban      0.624890

[5 rows x 33 columns]
```

Let's have a first look at the data

[12]:
```
fig, ax = plt.subplots(2,2, figsize=(15,10))

sns.histplot(df.state, ax = ax[0,0], color=rgb_1)
sns.histplot(df.county, ax = ax[0,1], color=rgb_1)
sns.histplot(df.geographic_division, ax = ax[1,0], color=rgb_1)
sns.histplot(df.census_region, ax = ax[1,1], color=rgb_1)

#adjust individual x label rotations for readability
```

```
ax[0,0].tick_params(axis='x', rotation = 80)
ax[0,1].tick_params(axis='x', rotation=90)
plt.suptitle('geographic distribution')
plt.tight_layout()
```



findings:

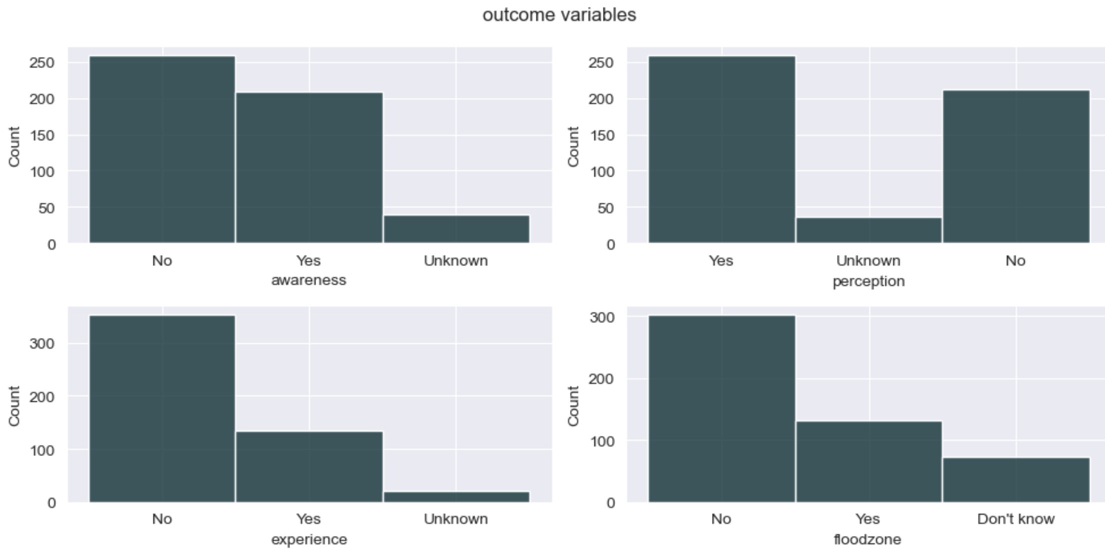
- only respondents in flood regions are included
- most respondents from florida
- pacific underrepresnted compared to atlantic

to understand spatial distribution of respondents (and other variables, we will have to add shape-files)

let's look into response variables first

[13]:
```
fig, ax = plt.subplots(2,2, figsize=(10,5))

sns.histplot(df.awareness, ax = ax[0,0], color=rgb_1)
sns.histplot(df.perception, ax = ax[0,1], color=rgb_1)
sns.histplot(df.experience, ax = ax[1,0], color=rgb_1)
sns.histplot(df.floodzone, ax = ax[1,1], color=rgb_1)

plt.suptitle('outcome variables')
```

```
plt.tight_layout() # avoid overlap of labels
```

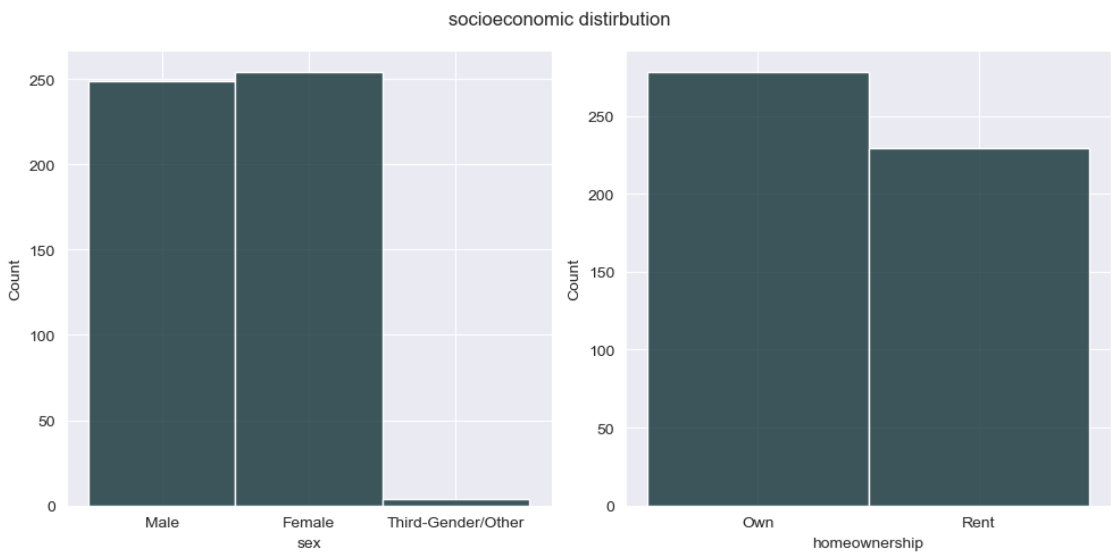


findings:

- ca 60% respondents do not live in a flood zone. That can in part be bc not every flood area is mapped by FEMA yet
- ca 20% has experienced flood before
- cfld_perception gives rich data distribution
- don't know is a small number. Can we maybe leave them out?

Let's change the variable coding and dtypes to numeric

[14]:
```
fig, ax = plt.subplots(1,2, figsize=(10,5))

sns.histplot(df.sex, ax = ax[0], color=rgb_1)
sns.histplot(df.homeownership, ax = ax[1], color=rgb_1)

plt.suptitle('socioeconomic distirbution')
plt.tight_layout() # avoid overlap of labels
```




```
[15]: df.sex.replace({"Male":0, "Female":1, 'Third-Gender/Other': np.nan}, inplace =␣
      ↪True)
      df.homeownership.replace({'Rent':0, 'Own':1}, inplace = True)
      df.rurality.replace({'Urban': 1, 'Rural': 0}, inplace=True)
```

```
[16]: variables = ['perception', 'awareness', 'experience', 'floodzone']
      dict = {
         'No': 0,
         'Yes': 1,
         'Unknown': np.nan,
         "Don't know": np.nan
      }
      df[variables] = df[variables].replace(dict)
```

```
[17]: dict = {'Less than $10,000':10000,
              '$10,000 to $14,999':12500,
              '$15,000 to $24,999':20000,
              '$25,000 to $34,999':30000,
              '$35,000 to $49,999':47500,
              '$50,000 to $74,999':62500,
              '$75,000 to $99,999':87500,
              '$100,000 to $149,999':125000,
              '$150,000 to $199,999':175000,
              '$200,000 or more':290000
              }
      df.income.replace(dict, inplace = True);
```

value for highest income bracket is representing median income in that bracket:

https://www.census.gov/programs-surveys/cps.html

https://www.census.gov/library/publications/2022/demo/p60-276.html

[18]:
```
dict = {'18-19': 18.5,
        '20-29': 25,
        '30-39': 35,
        '40-49': 45,
        '50-59': 55,
        '60-69': 65,
        '70-79': 75,
        '80+': 90
}
df.age.replace(dict, inplace = True);
```

[19]:
```
dict={'Less than high school diploma':0,
      'High school degree or diploma':1,
      'Some college, no degree':2,
      "Associate's degree":3,
      "Bachelor's degree":4,
      'Post graduate work/degree or professional degree':5
      }
df.education.replace(dict, inplace = True)
```

[20]:
```
dict={'$0' : 0,
      '$1 - $500':250,
      '$501 - $750':675,
      '$751 - $1,000':875,
      '$1,001 - $1,500':1250,
      '$1,501 - $2,000':1750,
      '$2,001 - $2,500':2250,
      '$2,501 - $3,000':2750,
      'More than $3,000':3000,
      "Don't know": np.nan
      }
df.rentmortgage.replace(dict, inplace = True)
```

[21]:
```
df.supplies.replace({'Blank': 0, 'Assembled or updated supplies': 1},␣
 ↪inplace=True)
df.insured.replace({'Blank': 0, 'Documented and insured property': 1},␣
 ↪inplace=True)
df.involved.replace({'Blank': 0, 'Got involved in my community': 1},␣
 ↪inplace=True)
df.learned_routes.replace({'Blank': 0, 'Learned my evacuation routes': 1},␣
 ↪inplace=True)
df.made_plan.replace({'Blank': 0, 'Made a plan': 1}, inplace=True)
df.made_safer.replace({'Blank': 0, 'Made my home safer': 1}, inplace=True)
```

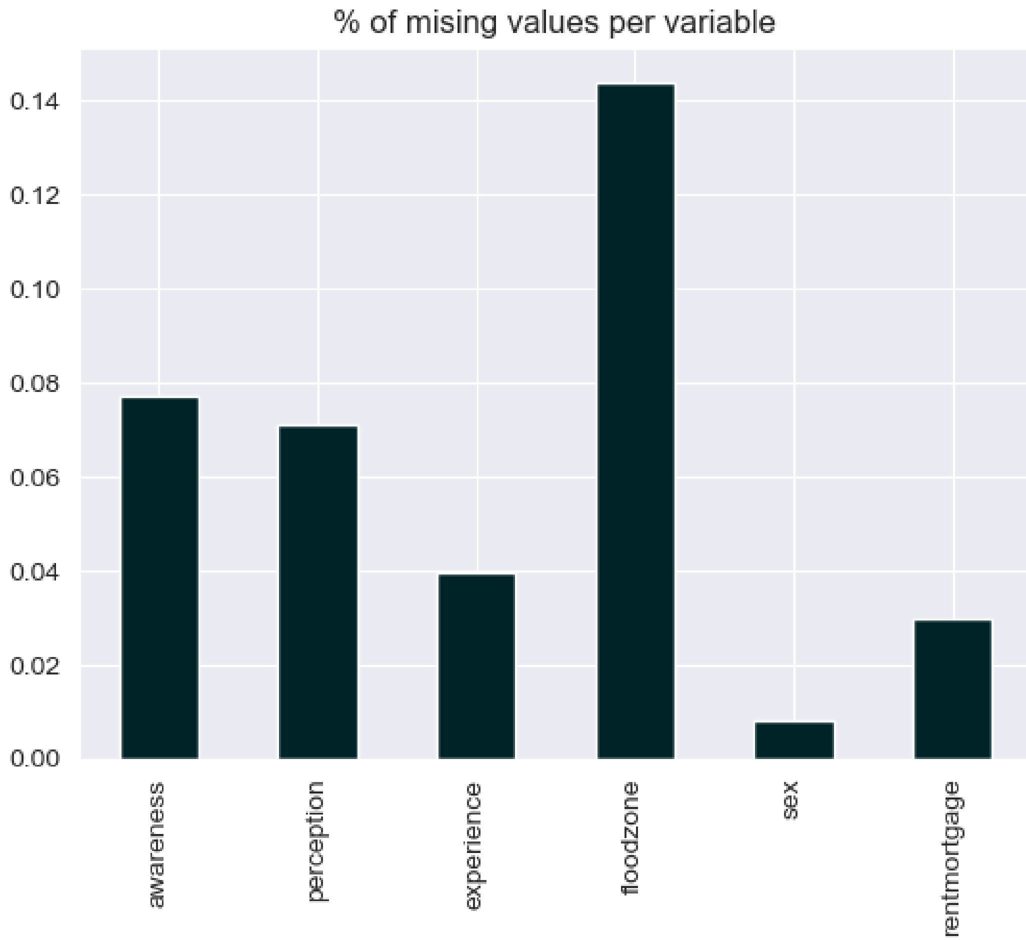
```
df.planned_neighbors.replace({'Blank': 0, 'Planned with neighbors': 1},␣
 ↪inplace=True)
df.practiced_drills.replace({'Blank': 0, 'Practiced emergency drills or habits':
 ↪ 1}, inplace=True)
df.documents.replace({'Blank': 0, 'Safeguarded documents': 1}, inplace=True)
df.rainy_day.replace({'Blank': 0, 'Saved for a rainy day': 1}, inplace=True)
df.alerts.replace({'Blank': 0, 'Signed up for alerts and warnings': 1},␣
 ↪inplace=True)
df.family_communication.replace({'Blank': 0, 'Tested family communication plan':
 ↪ 1}, inplace=True)
df.none.replace({'Blank': 0, 'None of the above': 1}, inplace=True)
df.dont_know.replace({'Blank': 0, "Don't know": 1}, inplace=True)

# let's also code as integer
variables = ['supplies','insured', 'involved', 'learned_routes', 'made_plan',
             'made_safer', 'planned_neighbors', 'practiced_drills', 'documents',
             'rainy_day', 'alerts','family_communication', 'none', 'dont_know']
df[variables] = df[variables].astype(int)
```

[22]:
```
# lets recode zipcodes as string and fill up leading zeros that have gone␣
 ↪missing
df.zipcode = df.zipcode.astype('string')

for i in df.index:
    if len(df.at[i,'zipcode']) == 4:
        df.at[i,'zipcode'] = str(0) + df.at[i,'zipcode']
    if len(df.at[i,'zipcode']) <= 4:
        print(i)
# classic lets try shit and pray loop... Make sure we fetched all exceptions...
```

[23]:
```
df.loc[:, df.isna().any()].isna().mean()
```

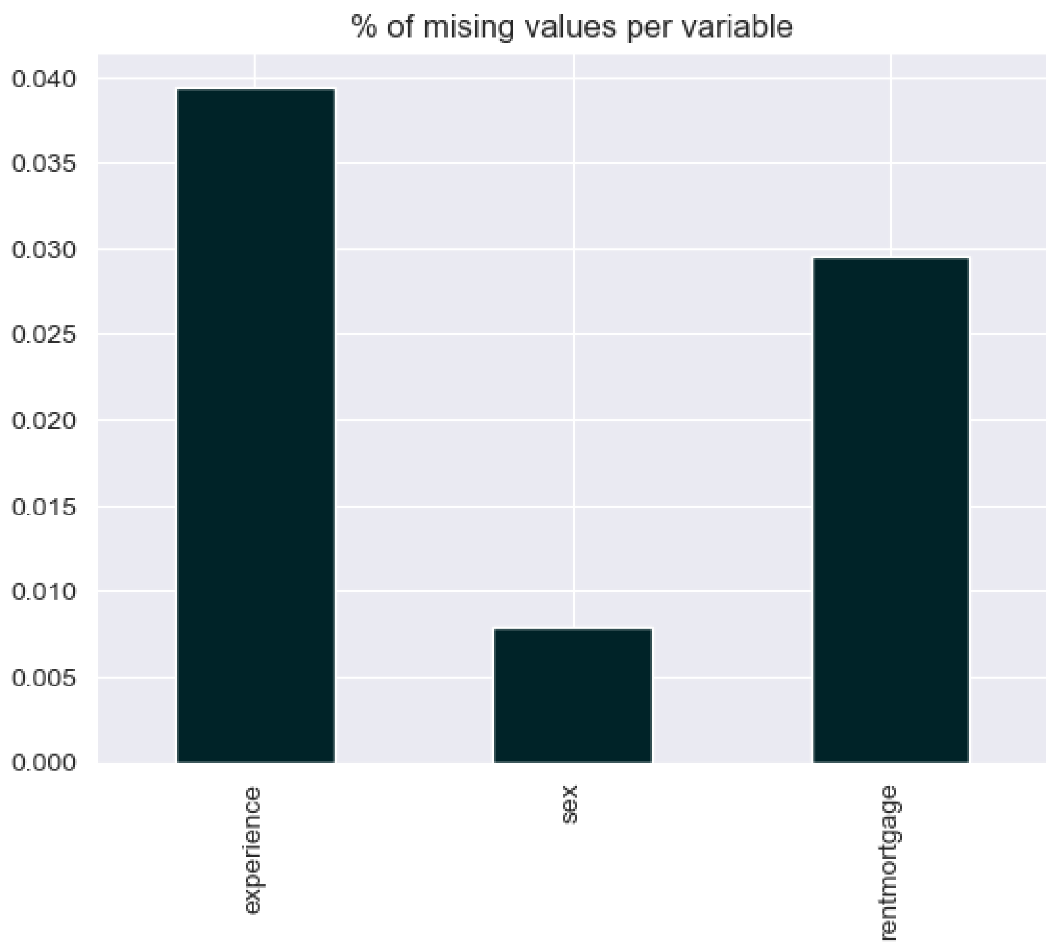
[23]:
```
awareness       0.076923
perception      0.071006
experience      0.039448
floodzone       0.143984
sex             0.007890
rentmortgage    0.029586
dtype: float64
```

[24]:
```
# let's see how many variables we have lost due to np.nan coding
df.loc[:, df.isna().any()].isna().mean().plot(kind='bar', title='% of mising␣
 ↪values per variable', color=rgb_1);
```



[25]:
```
df = df.drop(columns=['floodzone','awareness','perception'])
```

[26]:
```
df.loc[:, df.isna().any()].isna().mean().plot(kind='bar', title='% of mising␣
↪values per variable', color=rgb_1);
```



0.1.1 Double check this code block above!

[27]:
```
df.dropna(inplace=True)
```

[28]:
```
df.shape
```

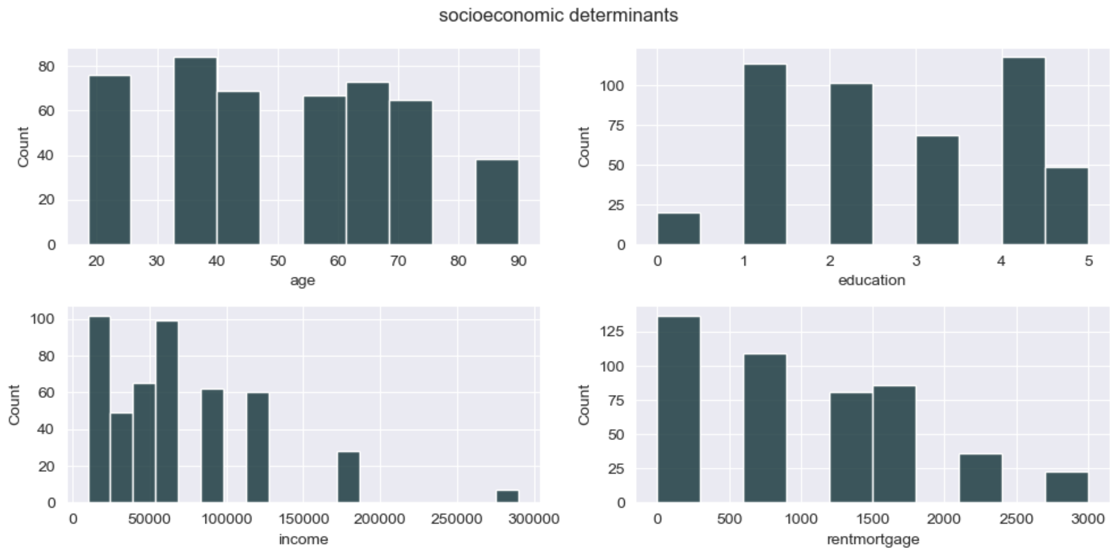
[28]: (472, 30)

0.2 Exploratory Analysis

Let's have a look at socioeconomic distributions

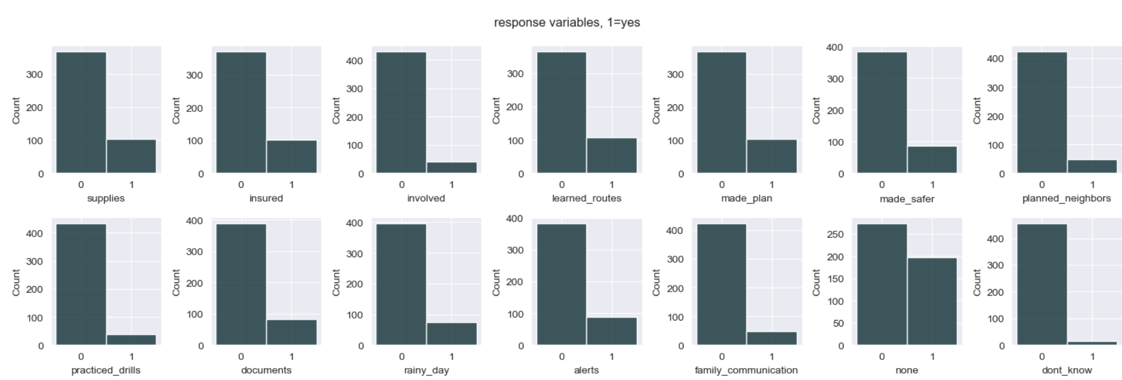
[29]:
```
fig, ax = plt.subplots(2,2, figsize=(10,5))

sns.histplot(df.age, ax = ax[0,0], color=rgb_1)
sns.histplot(df.education, ax = ax[0,1], color=rgb_1)
sns.histplot(df.income, ax = ax[1,0], color=rgb_1)
sns.histplot(df.rentmortgage, ax = ax[1,1], color=rgb_1)
```

```
plt.suptitle('socioeconomic determinants')
plt.tight_layout() # avoid overlap of labels
plt.savefig('../figures/unimodal/socioeconoimc_determinants.png', dpi=1000)
```



Let's have a look at adaptation measures

[30]:
```
fig, ax = plt.subplots(2,7, figsize=(15,5))
ax = ax.flatten()
for idx, var in enumerate(variables):
    sns.histplot(df[var], ax = ax[idx], discrete=True, color=rgb_1)
plt.suptitle('response variables, 1=yes')
plt.tight_layout()
plt.savefig('../figures/unimodal/response_distribution_n.png')
```



findings:

- 40% of respondents have implemented nothing
- almost all adaptation options are implemented equally often.

Let's look at some correlations

[31]:
```
variables = ['age', 'sex', 'income', 'education', 'rentmortgage']
spearman = pd.DataFrame(
    data = stats.spearmanr(df[variables])[0],
    index = variables,
    columns = variables
)
sns.heatmap(spearman, cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot = True)
plt.savefig('../figures/relations/socioeconomic_n.png', bbox_inches='tight',␣
  ↪dpi=1000)
```

findings:

- correlation among covariates are small
- notably, low correlation between age and income
- note relation between (education, rentmortgage) and age
- variables are nominal, correlation mathematically incorrect.

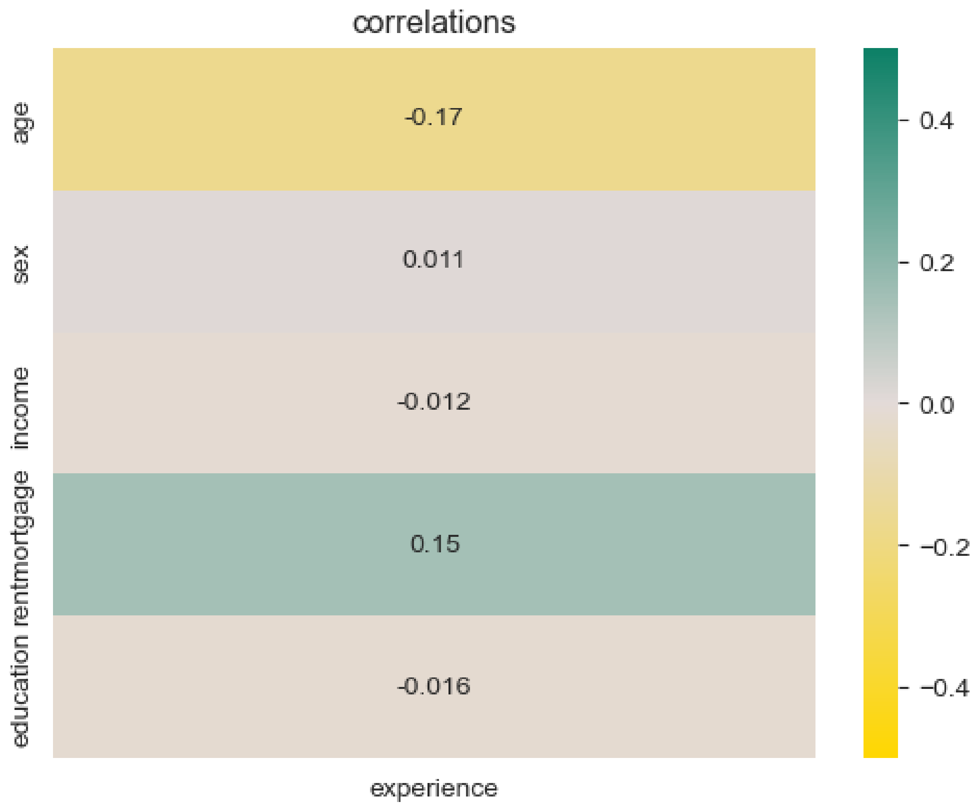
Let's map relationships between covariates and responses

[32]:
```
variables = ['experience']
index = ['age', 'sex', 'income', 'rentmortgage', 'education']
age = [np.corrcoef(df.age, df[var])[0,1] for var in variables]
sex = [np.corrcoef(df.sex, df[var])[0,1] for var in variables]
income = [np.corrcoef(df.income, df[var])[0,1] for var in variables]
rentmortgage = [np.corrcoef(df.rentmortgage, df[var])[0,1] for var in variables]
education = [np.corrcoef(df.education, df[var])[0,1] for var in variables]

cor_df = pd.DataFrame([age, sex, income, rentmortgage, education] , index =␣
 ↪index, columns = variables)
cor_df
```

[32]:

	experience
age	-0.168184
sex	0.011309
income	-0.012016
rentmortgage	0.145276
education	-0.015856

[33]:
```
fig, ax = plt.subplots()
fig = sns.heatmap(cor_df, cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
plt.title('correlations')
plt.savefig('../figures/relations/determinants_n.png', dpi=1000)
```



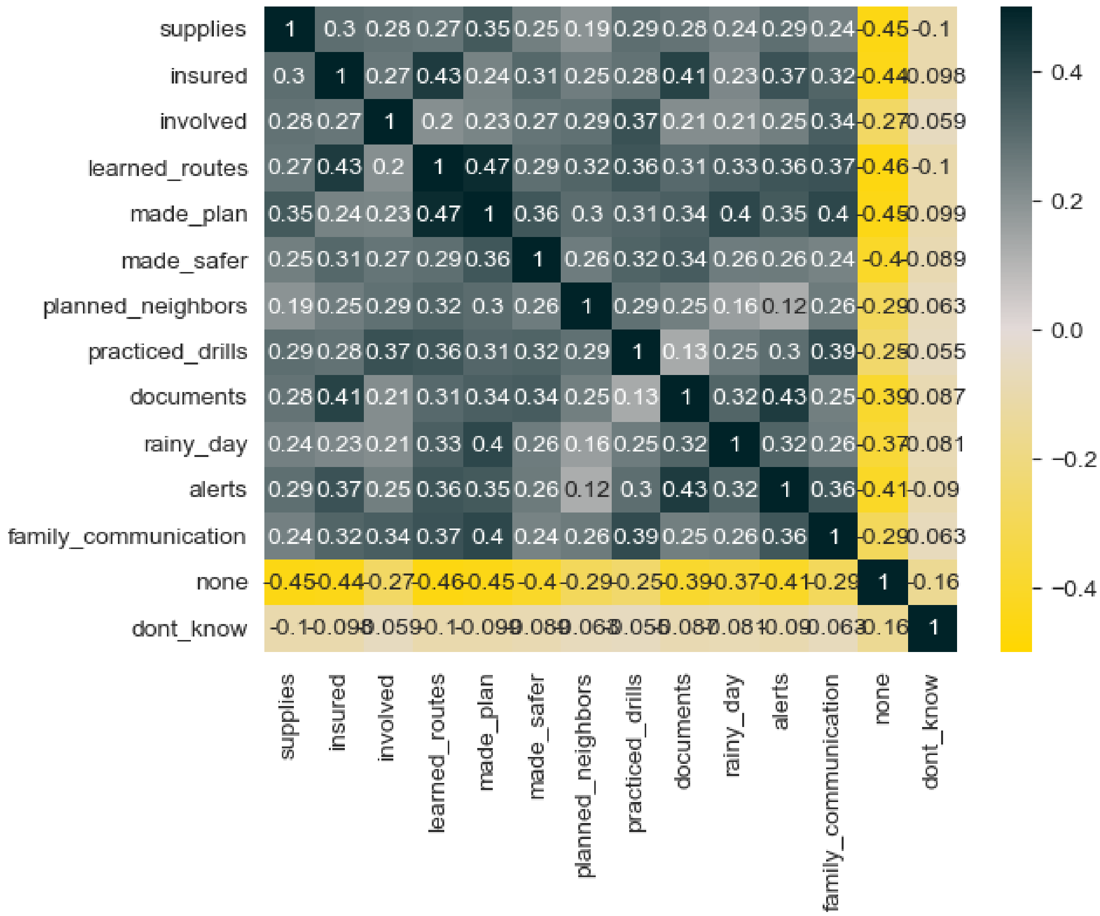
findings:

- older respondents are expecting less flooding
- older respondents are less likely to have experienced floodings???

Let's have a look at correlations between outcome variables

[34]:
```
variables = ['supplies', 'insured', 'involved', 'learned_routes', 'made_plan',
             'made_safer', 'planned_neighbors', 'practiced_drills',␣
 ↪'documents', 'rainy_day',
             'alerts', 'family_communication', 'none', 'dont_know']
sns.heatmap(df[variables].corr(),cmap=yellow_dark, vmin=-0.5, vmax=0.5,␣
 ↪annot=True)
```

[34]: <Axes: >



findings:

- all of the above correlate in same range: no specific links between specific types of adaptation
- learned_routs and insured correlate stronger
- documents and insured correlate stronger
- alerts and insured correlate stronger
- made_plan and learned_routes correlate stronger
- alerts and documents correlate stronger

0.3 Spatial Mapping

[35]:
```
path = "/Users/philip/Documents/ESE/ESE_thesis/flood_experience/data/shapefiles/
↪tl_2024_us_zcta520.shp"

shp_gdf = gpd.read_file(path)
```

```
shp_gdf = shp_gdf.
    ↪drop(columns=['ZCTA5CE20','GEOIDFQ20','CLASSFP20','MTFCC20','FUNCSTAT20','ALAND20','AWATER2
```

[36]:
```
# lets merge it baby
shp_gdf= shp_gdf.rename(columns={'GEOID20':'zipcode'})
gdf = df.merge(shp_gdf, on = 'zipcode', how = 'left')
gdf = gpd.GeoDataFrame(gdf, geometry = gdf.geometry)
```

[37]:
```
# adjust crs to cx requirements (Web Mercator)
gdf = gdf.to_crs(epsg=3857)
gdf.crs
```

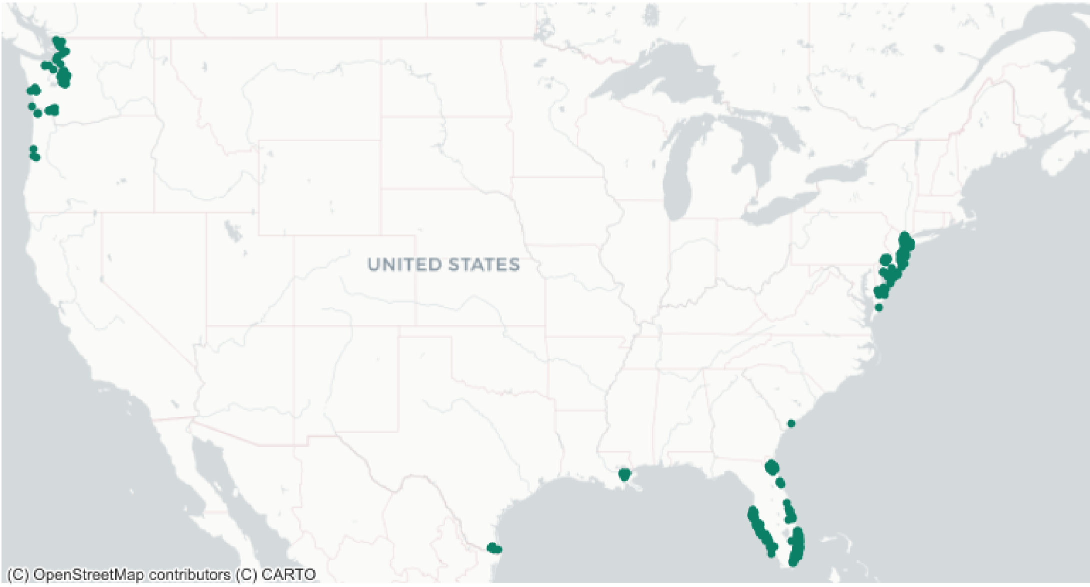
[37]:
```
<Projected CRS: EPSG:3857>
Name: WGS 84 / Pseudo-Mercator
Axis Info [cartesian]:
- X[east]: Easting (metre)
- Y[north]: Northing (metre)
Area of Use:
- name: World between 85.06°S and 85.06°N.
- bounds: (-180.0, -85.06, 180.0, 85.06)
Coordinate Operation:
- name: Popular Visualisation Pseudo-Mercator
- method: Popular Visualisation Pseudo Mercator
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

[38]:
```
gdf.shape
```

[38]:
```
(472, 31)
```

[39]:
```
us_bounds = (-14000000, 2800000, -7000000, 6500000)

# Let's switch to point geometries so that we can increase the marker size␣
    ↪manually
gdf_points = gdf.copy()
gdf_points['geometry'] = gdf_points.centroid

fig, ax = plt.subplots(figsize=(10,10))
gdf_points.plot(ax=ax, color=rgb_2, alpha=1, markersize=10)
ax.set_xlim(us_bounds[0], us_bounds[2])  # Longitude limits
ax.set_ylim(us_bounds[1], us_bounds[3])  # Latitude limits
cx.add_basemap(ax, source=cx.providers.CartoDB.Positron)
ax.set_axis_off()
plt.title('spatial distribution of survey responses')
plt.savefig('../figures/spatial/us_map.png', dpi=1000)
```

spatial distribution of survey responses



findings:

- Many flood regions (California & mid-East Coast) have no responses in the 2023 data
- focus regions will be washington/ oregon, florida, new jersey/ pennsylvania/ delaware/ virginia

to do:

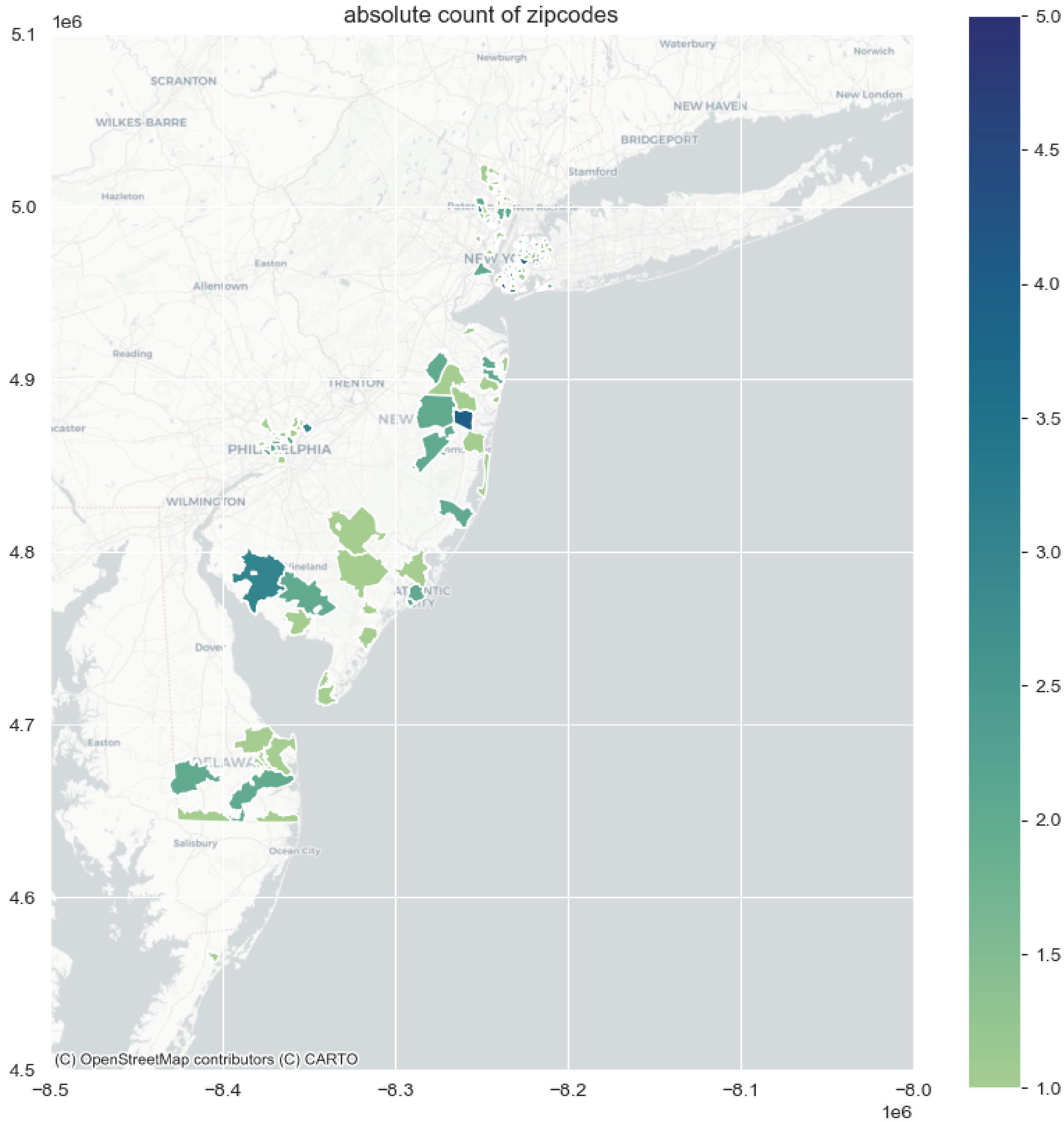
- check response distribution against other years

[40]:
```
# Let's add a column to our dataframe that counts total occurence of zipcodes
zip_counts = df.groupby(by='zipcode').size()
zip_counts = pd.DataFrame(zip_counts, columns=['zip_count'])
gdf = gdf.merge(zip_counts, on = 'zipcode', how='left')
```

[41]:
```
# export the data
path = '/Users/philip/Documents/ESE/ESE_thesis/flood_experience/data/export/
↪clean_n.csv'
gdf.to_csv(path, index=False)
```

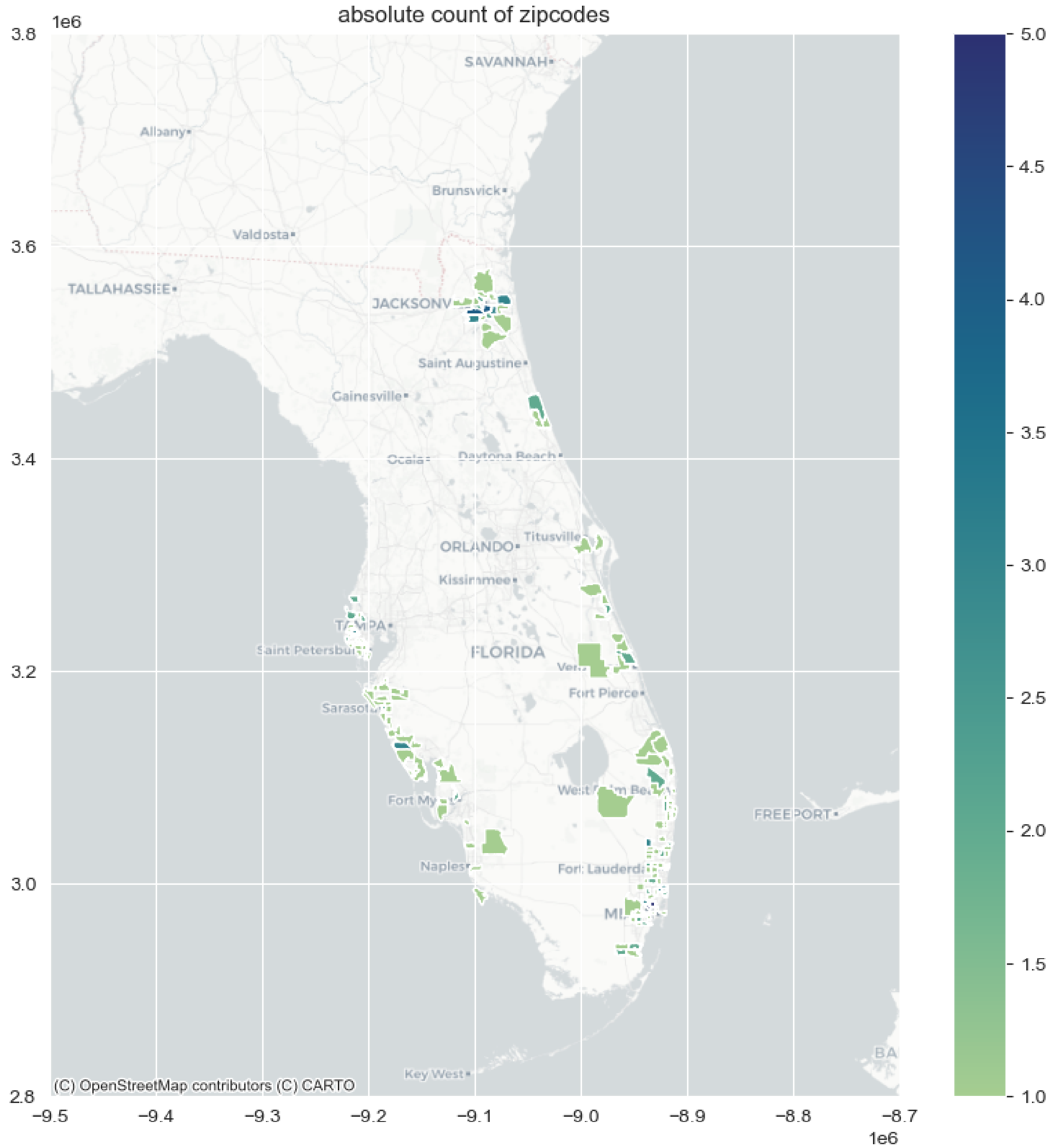
[42]:
```
# new jersey
bounds = (-8500000, 4500000, -8000000, 5100000)

fig, ax = plt.subplots(figsize=(10,10))
gdf.plot(ax=ax, cmap='crest', alpha=1, column='zip_count', legend=True)
ax.set_xlim(bounds[0], bounds[2])  # Longitude limits
ax.set_ylim(bounds[1], bounds[3])  # Latitude limits
cx.add_basemap(ax, source=cx.providers.CartoDB.Positron)
```

```
plt.title('absolute count of zipcodes')
plt.savefig('../figures/spatial/density/newjersey_zips_density.png', dpi=1000)
```



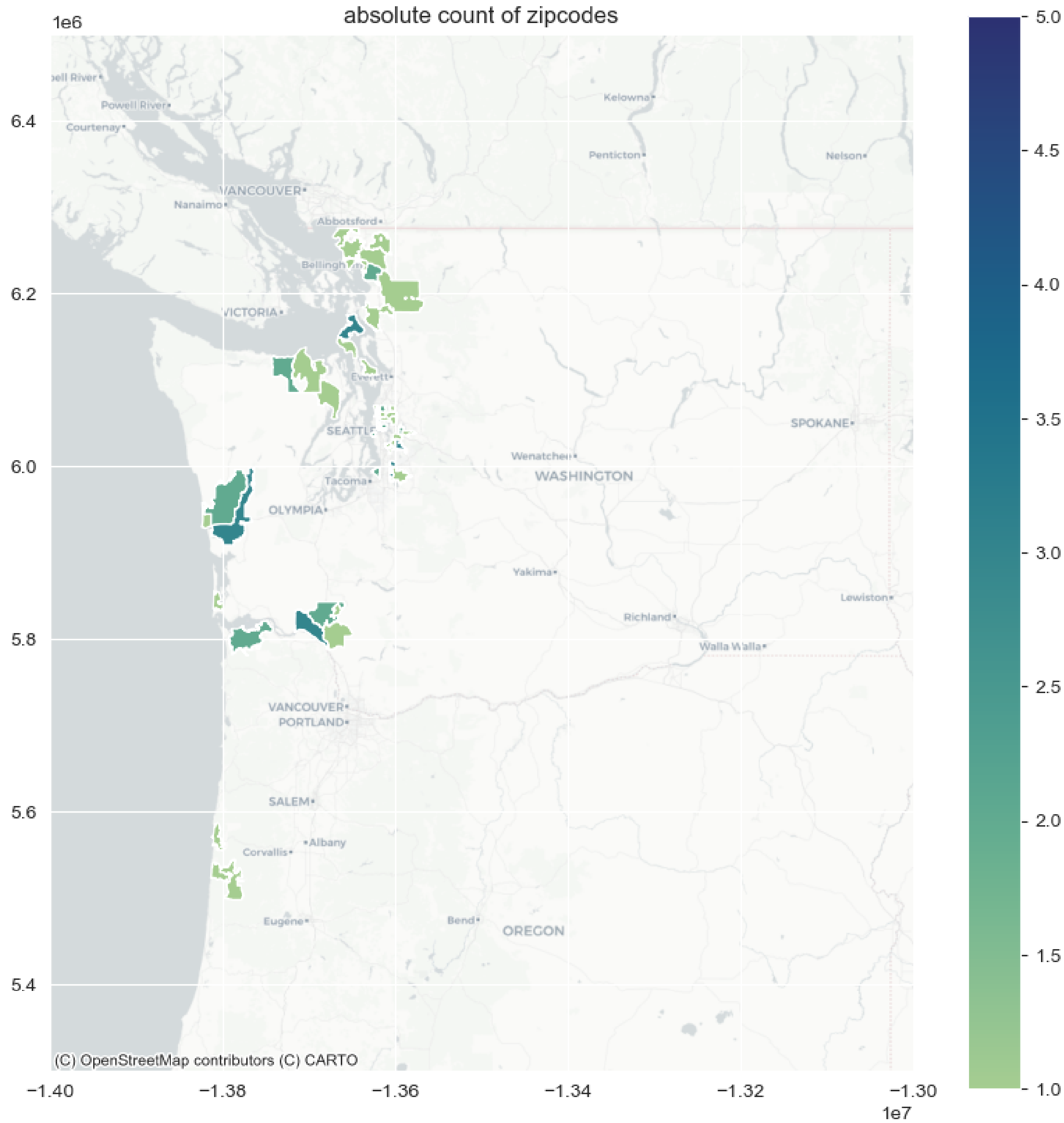
[43]:
```
# florida
bounds = (-9500000, 2800000,  -8700000, 3800000)

fig, ax = plt.subplots(figsize=(10,10))
gdf.plot(ax=ax, cmap='crest', alpha=1, column='zip_count', legend=True)
ax.set_xlim(bounds[0], bounds[2])  # Longitude limits
ax.set_ylim(bounds[1], bounds[3])  # Latitude limits
cx.add_basemap(ax, source=cx.providers.CartoDB.Positron)
```

```
plt.title('absolute count of zipcodes')
plt.savefig('../figures/spatial/density/florida_zips_density.png', dpi=1000)
```



[44]:
```
# seattle
bounds = (-14000000, 5300000, -13000000, 6500000)

fig, ax = plt.subplots(figsize=(10,10))
gdf.plot(ax=ax, cmap='crest', alpha=1, column='zip_count', legend=True)
ax.set_xlim(bounds[0], bounds[2])  # Longitude limits
```

```python
ax.set_ylim(bounds[1], bounds[3])  # Latitude limits
cx.add_basemap(ax, source=cx.providers.CartoDB.Positron)
plt.title('absolute count of zipcodes')
plt.savefig('../figures/spatial/density/seattle_zips_density.png', dpi=1000)
```



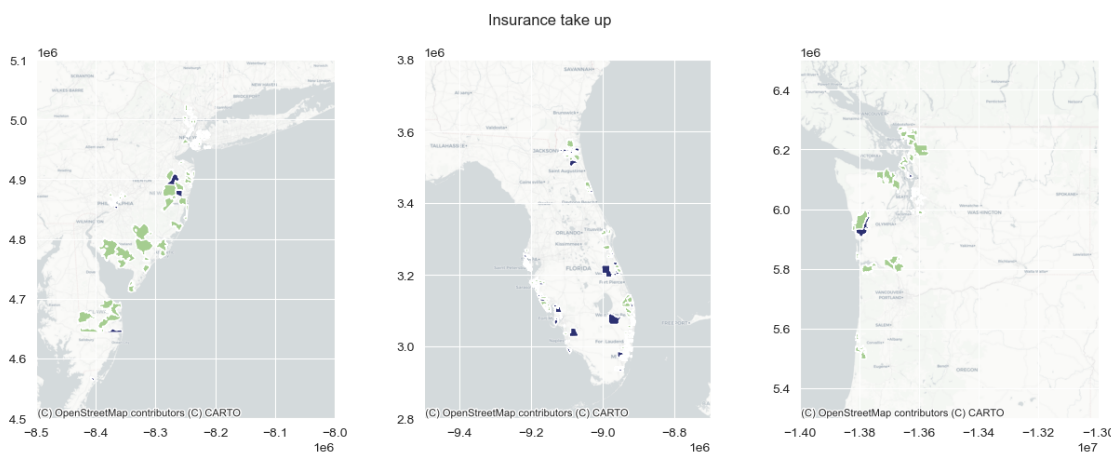
Findings:

- highest count of repsonses in one zipcode is 5
- overall, response rate spread very thin across space, very evenly
- most responses are in florida (see above too) but are evenly dispersed in space

- spatial interaction might be hard to fetch with such low data density
- LISA plots / spatial autocorrelation not making sense anymore?

Let's search for seperating equilibria next

[45]:
```
# let's plot insurance takeup

bounds = [(-8500000, 4500000, -8000000, 5100000),       #new jersey
          (-9500000, 2800000,  -8700000, 3800000),      #florida
          (-14000000, 5300000, -13000000, 6500000)]     #seattle

fig, ax = plt.subplots(1,3, figsize=(15,5))

for idx, var in enumerate(bounds):
    gdf.plot(ax=ax[idx], cmap='crest', column='insured', categorical=True)
    ax[idx].set_xlim(bounds[idx][0], bounds[idx][2])
    ax[idx].set_ylim(bounds[idx][1], bounds[idx][3])
    cx.add_basemap(ax[idx], source=cx.providers.CartoDB.Positron)

plt.suptitle('Insurance take up')
plt.savefig('../figures/spatial/density/insurance.png', dpi=1000)
```



findings:

- insurance take up is much more pronounced in florida, compared to seattle and new jersey
- first hint at pooling equilibrium
- lets see if there are counfounding factors?

See prints: 3by3 plot

findings:

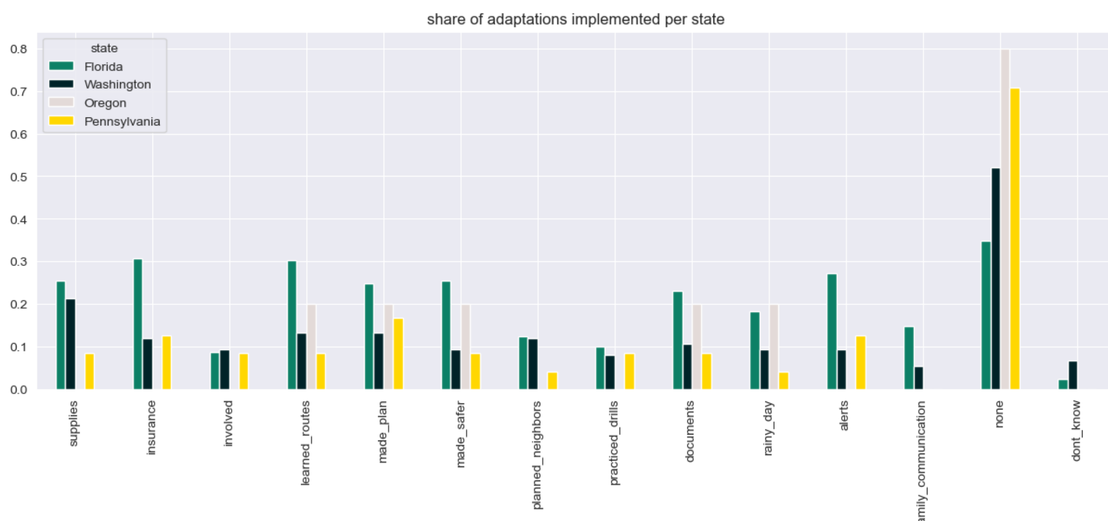
- experience seems to correlate with insurance take up

- when you know that you are in a flood zone, you are more likely linsured in new jersey and florida, but not in seattle!
- in seattle people are having higher perception but no experience -> no insurance take up
- in florida we have high perception, high experience, and high take up

Let's confirm difference in share of adaptaion outcomes

[46]:
```
adaptations = gdf.groupby('state').agg(
    supplies = ('supplies','mean'),
    insurance = ('insured','mean'),
    involved = ('involved','mean'),
    learned_routes = ('learned_routes','mean'),
    made_plan =  ('made_plan', 'mean'),
    made_safer = ('made_safer', 'mean'),
    planned_neighbors = ('planned_neighbors', 'mean'),
    practiced_drills = ('practiced_drills', 'mean'),
    documents = ('documents', 'mean'),
    rainy_day = ('rainy_day', 'mean'),
    alerts = ('alerts', 'mean'),
    family_communication = ('family_communication', 'mean'),
    none = ('none', 'mean'),
    dont_know = ('dont_know', 'mean')
    ).transpose()
```

[70]:
```
adaptations[['Florida', 'Washington', 'Oregon', 'Pennsylvania']].plot(
    kind='bar',
    figsize=(15,5),
    title='share of adaptations implemented per state',
    cmap=discrete)
plt.savefig('../figures/unimodal/adpataions_per_region_n.
 ↪png',bbox_inches='tight', dpi=1000)
```



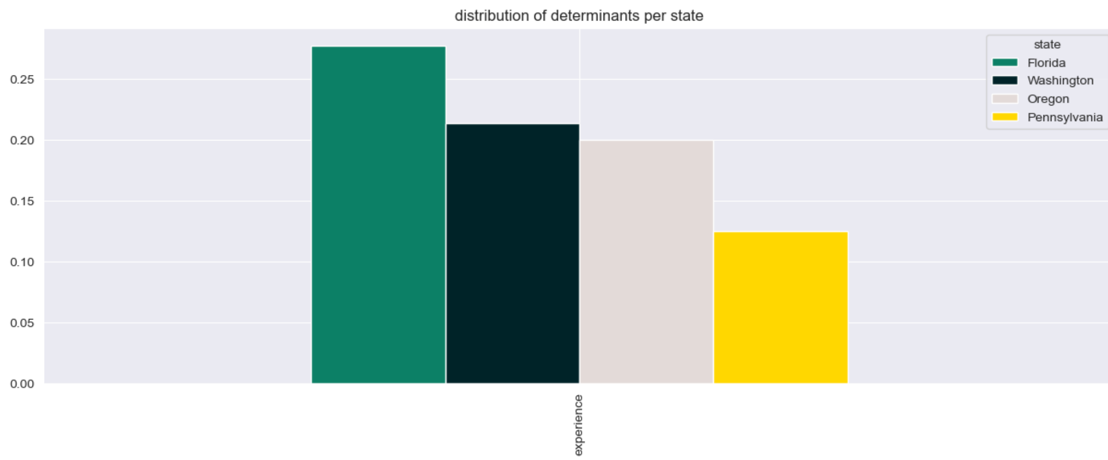
findings:

- numbers might still be a bit skewed: FLorida and Washington are dispersed spatially more than New York
- Florida has generally higher share of adaptations implemented -> seperating equilibrium?

Let's look into candidates for independent variables

[72]:
```
independent = gdf.groupby('state').agg(
    experience = ('experience', 'mean'),
    ).transpose()
```

[75]:
```
independent[['Florida', 'Washington', 'Oregon', 'Pennsylvania']].plot(
    kind='bar',
    figsize=(15,5),
    title='distribution of determinants per state',
    cmap=discrete)
plt.savefig('../figures/unimodal/determinants_per_region_n.png', dpi=1000)
```



Let's drill down into focus regions. This will allow us to investigate possible spatial interactions

[50]:
```
# let's build seperate frames for each focus region
seattle = gdf[(gdf.county == 'King')]

newyork = gdf[(gdf.county == 'Kings') |
              (gdf.county == 'Hudson') |
              (gdf.county == 'Queens')]

jacksonville = gdf[(gdf.county == 'Duval')]
```

```python
miami = gdf[(gdf.county == 'Broward') |
            (gdf.county == 'Miami-Dade') |
            (gdf.county == 'Palm Beach') |
            (gdf.county == 'Martin')]

sarasota = gdf[(gdf.county == 'Sarasota') |
               (gdf.county == 'Charlotte') |
               (gdf.county == 'Lee') |
               (gdf.county == 'Pinellas') |
               (gdf.county == 'Collier')]

# let's add a column that indicates the focus region
seattle["focus_region"] = "Seattle"
newyork["focus_region"] = "New York"
jacksonville["focus_region"] = "Jacksonville"
miami["focus_region"] = "Miami"
sarasota["focus_region"] = "Sarasota"

# let's put all together
focus_regions = pd.concat([seattle, newyork, jacksonville, miami, sarasota])
```

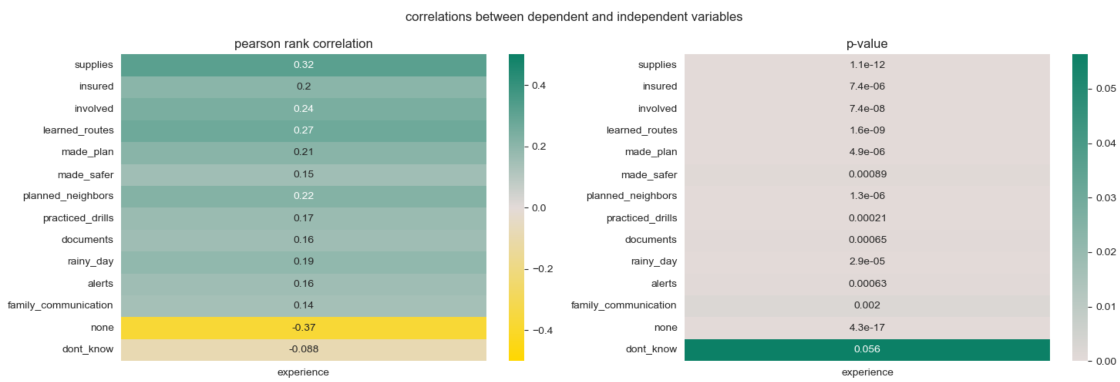
0.4 Relationships

[51]:
```python
# Let's explore correlations on the focus_region level. We hope for differences␣
↪in correlations between focus regions
variables = [ 'perception', 'experience', 'supplies', 'insured', 'involved',␣
↪'learned_routes',
             'made_plan', 'made_safer', 'planned_neighbors',␣
↪'practiced_drills', 'documents', 'rainy_day', 'alerts',␣
↪'family_communication',
              'none', 'dont_know' ,'age', 'sex','education', 'homeownership',␣
↪'income', 'rentmortgage','rurality' ,'zip_count']
```

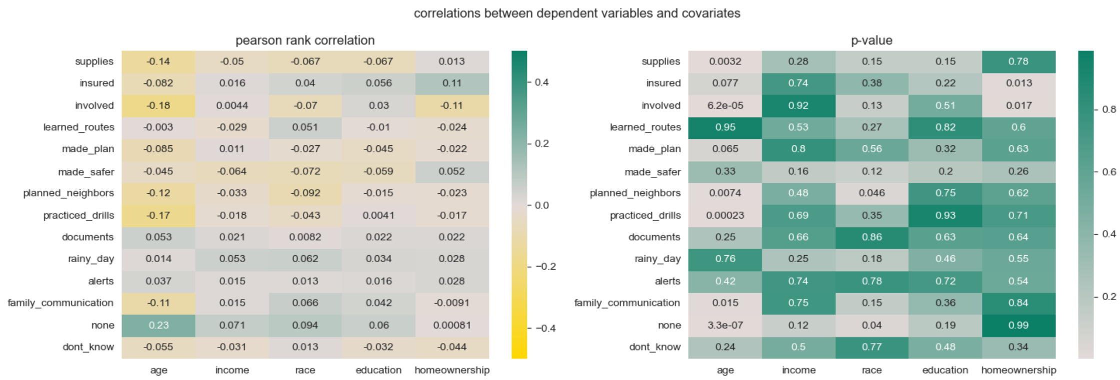
[52]:
```python
dependent = ['supplies', 'insured', 'involved', 'learned_routes', 'made_plan',␣
↪'made_safer', 'planned_neighbors',
            'practiced_drills', 'documents', 'rainy_day', 'alerts',␣
↪'family_communication', 'none', 'dont_know']
independent = ['experience']
covariate = ['age', 'income', 'race', 'education', 'homeownership']
```

[53]:
```python
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(df[var], df[v]) for v in independent]␣
↪#stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(df[var], df[v]) for v in covariate]
```

[54]:
```python
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True) # access spearman r with lambda function
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True) # access p-value with lambda function
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/full.png')
```

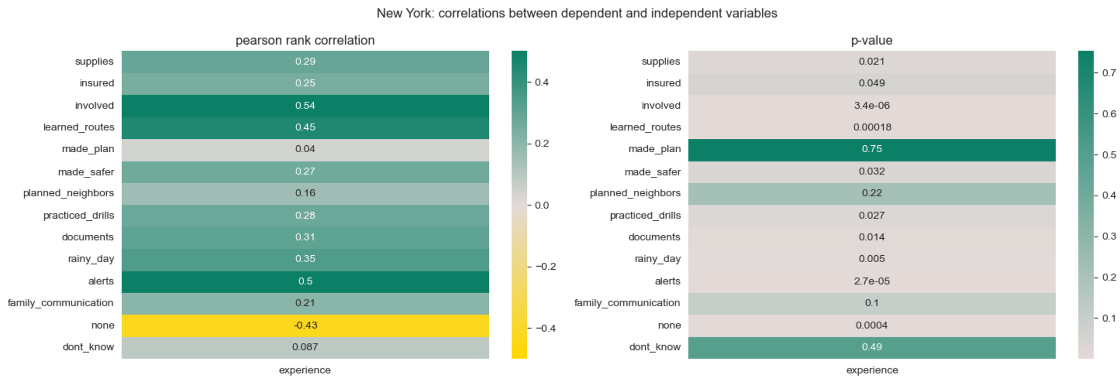


[55]:
```python
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_cov.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True) # access spearman r with lambda function
sns.heatmap(data=dep_cov.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True) # access p-value with lambda function
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('correlations between dependent variables and covariates')
plt.tight_layout()
plt.savefig('../figures/relations/covariates_full.png')
```

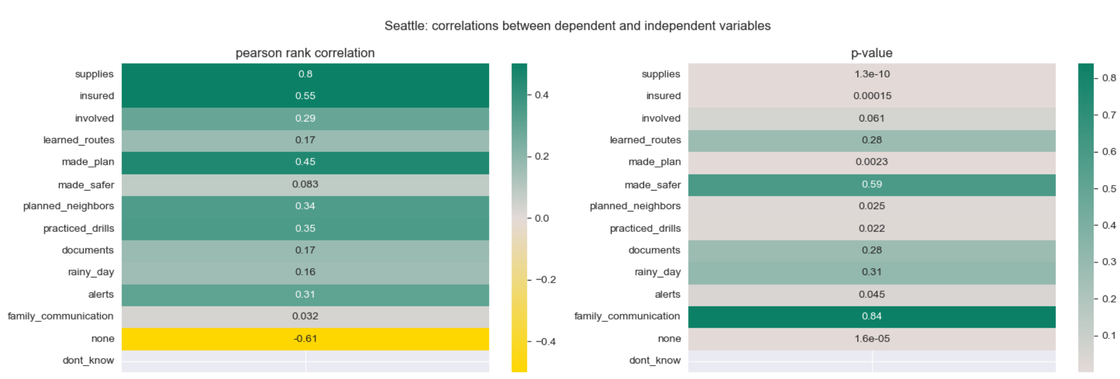


Let's compare correlations across focus regions

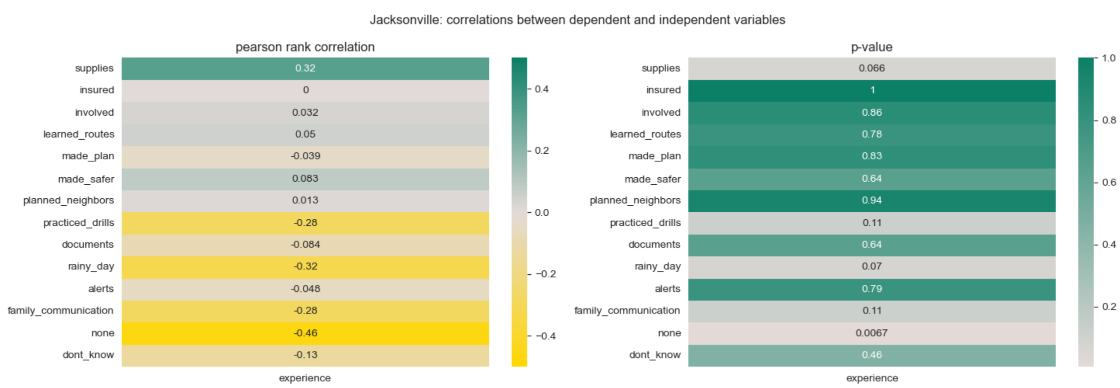
```
[56]: # New York
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(newyork[var], newyork[v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(newyork[var], newyork[v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('New York: correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/newyork.png')
```




```
[57]: # Seattle
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(seattle[var], seattle[v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(seattle[var], seattle[v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('Seattle: correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/seattle.png')
```

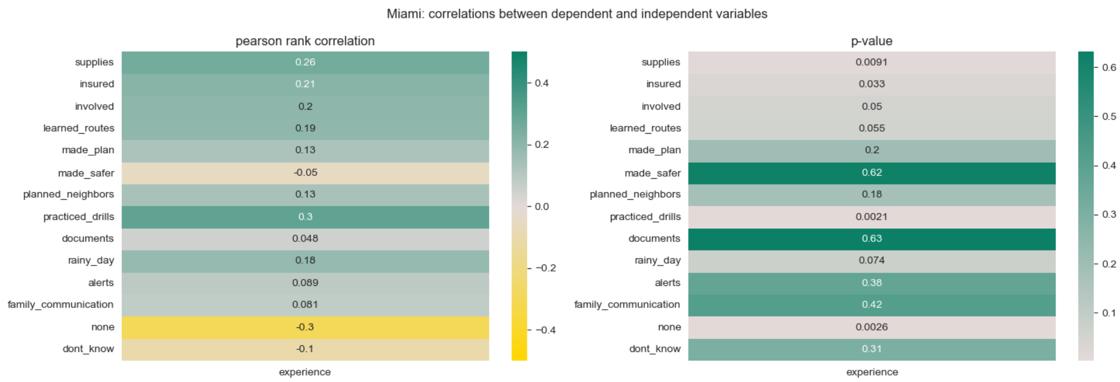


```
[58]: # Jacksonville
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(jacksonville[var], jacksonville[v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(jacksonville[var], jacksonville[v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('Jacksonville: correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/jacksonville.png')
```



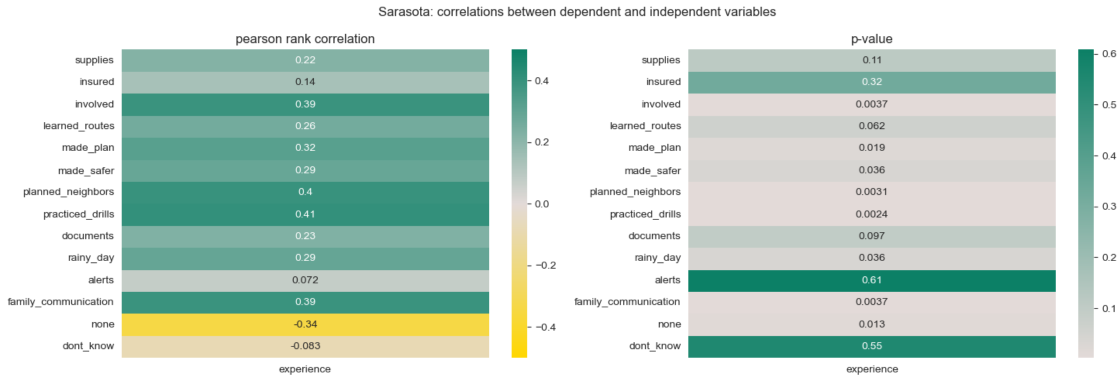

```
[59]: # Miami
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(miami[var], miami[v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(miami[var], miami[v]) for v in covariate]
```

```
#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('Miami: correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/miami.png')
```



[60]:
```
# Sarasota
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(sarasota[var], sarasota[v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(sarasota[var], sarasota[v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap=sequential, annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('Sarasota: correlations between dependent and independent variables')
plt.tight_layout()
```

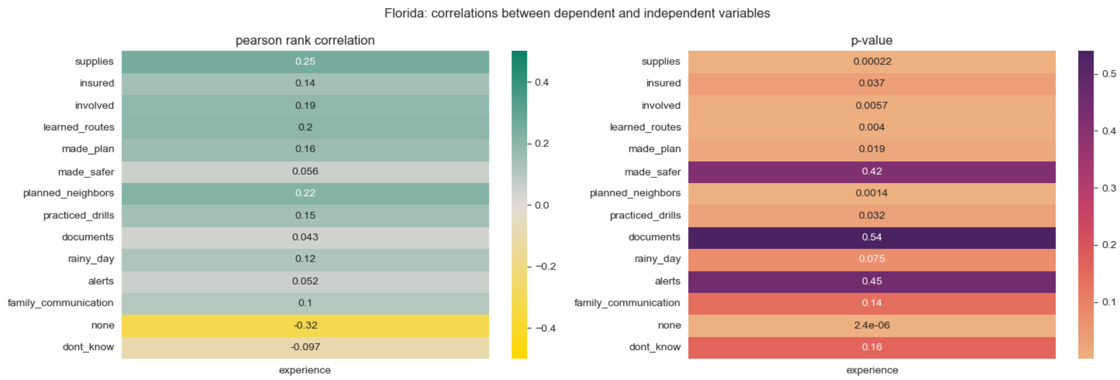
```
plt.savefig('../figures/relations/sarasota.png')
```



Adaptation Fatigue: - In Jacksonville experience seems to be much lower correlated with certain adaptaion variables than in York. - Weaker effect but same effect direction in Miami. - We can hypothesize which variables are impacted by adaptaion fatigue and which are not

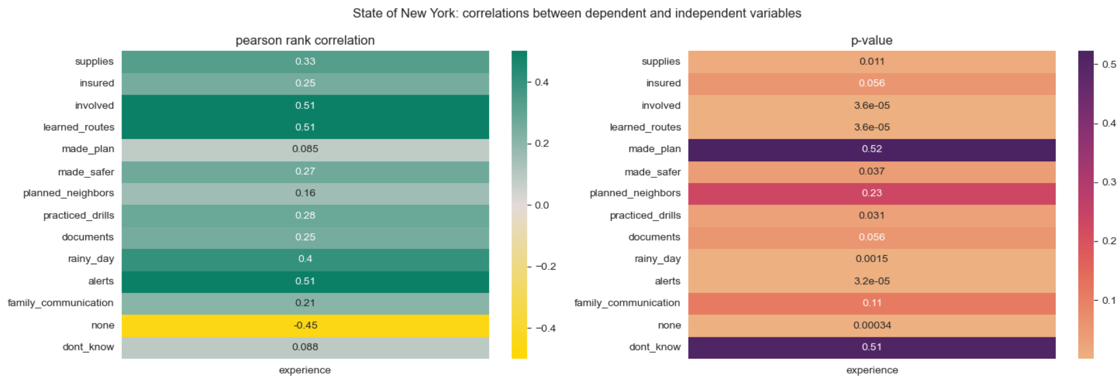
Let's check the hypothesis against larger regions (Florida v New York)

[61]:
```
# Florida
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(df.loc[df['state'] == 'Florida',var], df.
 ↪loc[df['state'] == 'Florida', v]) for v in independent] #stats.spearman␣
 ↪returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(df.loc[df['state'] == 'Florida',var], df.
 ↪loc[df['state'] == 'Florida', v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0],␣
 ↪cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1],␣
 ↪cmap='flare', annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('Florida: correlations between dependent and independent␣
 ↪variables')
plt.tight_layout()
plt.savefig('../figures/relations/florida.png')
```

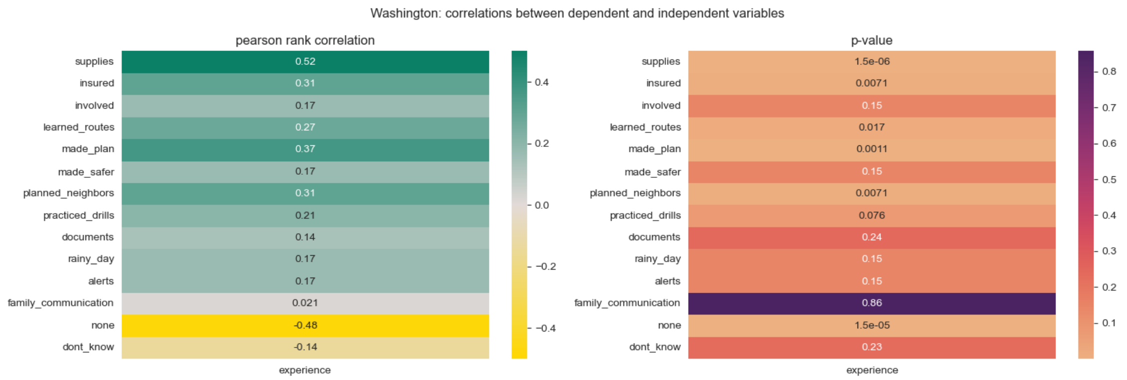


[62]:

```python
# Florida
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(df.loc[df['state'] == 'New York',var], df.loc[df['state'] == 'New York', v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(df.loc[df['state'] == 'New York',var], df.loc[df['state'] == 'New York', v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap='flare', annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('State of New York: correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/State_of_New_York.png')
```



[63]:
```python
# Washington
dep_ind = pd.DataFrame(columns=dependent, index=independent)
dep_cov = pd.DataFrame(columns=dependent, index=covariate)
for idx, var in enumerate(dependent):
    dep_ind[var] = [stats.spearmanr(df.loc[df['state'] == 'Washington',var], df.loc[df['state'] == 'Washington', v]) for v in independent] #stats.spearman returns tuple(statistic, p-value)
    dep_cov[var] = [stats.spearmanr(df.loc[df['state'] == 'Washington',var], df.loc[df['state'] == 'Washington', v]) for v in covariate]

#plot
fig, ax = plt.subplots(1,2, figsize=(15,5))
sns.heatmap(data=dep_ind.applymap(lambda x: x[0]).transpose(), ax=ax[0], cmap=yellow_bright, vmin=-0.5, vmax=0.5, annot=True)
sns.heatmap(data=dep_ind.applymap(lambda x: x[1]).transpose(), ax=ax[1], cmap='flare', annot=True)
ax[0].set_title('pearson rank correlation')
ax[1].set_title('p-value')
plt.suptitle('Washington: correlations between dependent and independent variables')
plt.tight_layout()
plt.savefig('../figures/relations/Washington.png')
```



[64]:

```
#Let's drill into zipcode level adaptation distribution per focus region
florida_adaptations = gdf.groupby('zipcode').agg(
    supplies = ('supplies','sum'),
    insurance = ('insured','sum'),
    involved = ('involved','sum'),
    learned_routes = ('learned_routes','sum'),
    made_plan =  ('made_plan', 'sum'),
    made_safer = ('made_safer', 'sum'),
    planned_neighbors = ('planned_neighbors', 'sum'),
    practiced_drills = ('practiced_drills', 'sum'),
    documents = ('documents', 'sum'),
    rainy_day = ('rainy_day', 'sum'),
    alerts = ('alerts', 'sum'),
    family_communication = ('family_communication', 'sum'),
    none = ('none', 'sum'),
    dont_know = ('dont_know', 'sum')
)
```

[65]:

```
newjersey_adaptations = gdf.groupby('zipcode').agg(
    supplies = ('supplies','sum'),
    insurance = ('insured','sum'),
    involved = ('involved','sum'),
    learned_routes = ('learned_routes','sum'),
    made_plan =  ('made_plan', 'sum'),
    made_safer = ('made_safer', 'sum'),
    planned_neighbors = ('planned_neighbors', 'sum'),
    practiced_drills = ('practiced_drills', 'sum'),
    documents = ('documents', 'sum'),
    rainy_day = ('rainy_day', 'sum'),
    alerts = ('alerts', 'sum'),
    family_communication = ('family_communication', 'sum'),
    none = ('none', 'sum'),
    dont_know = ('dont_know', 'sum')
```

```
)
```

[66]:
```
Florida = df[df['state']=='Florida']
NewYork = df[df['state']=='New York']
```

[67]:
```
Washington = df[df['state'] == 'Washington']
Washington.shape
```

[67]: (75, 30)

[68]:
```
Florida.shape
```

[68]: (209, 30)

[69]:
```
NewYork.shape
```

[69]: (59, 30)