- Missing values
- Recoding
- Lab5
- Secondary variables
- Grouping variables
- lab 6

- One of the later steps in data management is evaluating whether you might want to create secondary variables.
- Secondary variables may include information from two or more primary variables.
- They can be created using a mathematical or logical operation on two or more variables.
- For our example we want to know the number of cigarettes smoked per month.
- We know how often each respondent smoked S3AQ3B1

- We can create a new variable USFREQMO which will give us an estimate of the quantity smoked per month.
- Again we use the variable S3AQ3B1 to estimate the number of cigarettes smoked in a month.
- Value 1: Everyday could estimate to 30 cigarettes per month
- Value 2: 5-6 days per week could estimate to 22 cigarettes per month
- Etc. for values 3, 4, 5, and 6

- These are estimates but they still capture the quantitative nature of the measure and also keep individuals ordered in terms of the frequency with which they smoke.
- The new variable is called USFREQMO

```
Recode1 = {1: 30, 2: 22, 3: 14, 4: 5, 5: 2.5, 6:1}
Sub2['USFREQMO'] = sub2['S3AQ3B1'].map(recode2)
```

- While it is a categorical variable we actually get more information out of it than we had originally been given.
- We can then request the frequency table for the sample of 1,706 young adults (>=18 and <=25) who smoked in the past year. This shows us more clearly the numbers and percentages of approximate number of days per month.

```
counts for USFREQMO
30.0
      1320
14.0
       91
5.0
       88
1.0
       71
                       print('counts for USFREQMO')
22.0
       68
2.5
       65
                       p7=sub2[['USFREQMO'].value counts(sort=False, dropna=False)
NaN
Name: USFREQMO, dtype: int64
percentages for USFREQMO
                       print(p7)
     0.775103
14.0
     0.053435
5.0
     0.051674
                       print('percentages for USFREQMO')
1.0
     0.041691
22.0
     0.039930
2.5
     0.038168
                       p8=sub2['USFREQMO'].value counts(sort=False, normalize=True)
Name: USFREQMO, dtype: float64
                       print(p8)
```

- We now know the estimated number of days smoked in a month in our new variable USFREQMO
- We also have the variable S3AQ3C1 which holds the usual quantity when smoked. I-98 cigarettes, 99 unknown and blank.
- If we want to estimate the number of cigarettes that participants smoked per month it would make sense to multiply the two variables and get a product that represents the number of cigarettes smoked per month.
- The new variable will be called NUMCIGMO_EST

```
sub2['NUMCIGMO_EST'] = sub2['USFREQMO'] * sub2['S3AQ3C1']
sub3= sub2[['IDNUM','S3AQ3C1','USFREQMO','NUMCIGMO_EST']]
sub3.head(25)
What does this do?
```

In [In [8]: subset3.head(25)					
Out[8]:						
	IDNUM	S3AQ3C1	USFREQMO	NUMCIGMO_EST		
20	21	3	30.0	90.0		
76	77	3	22.0	66.0		
102	103	10	30.0	300.0		
121	122	10	30.0	300.0		
135	136	20	30.0	600.0		
149	150	5	30.0	150.0		
154	155	8	30.0	240.0		
173	174	1	30.0	30.0		
177	178	10	30.0	300.0		
183	184	20	30.0	600.0		
187	188	2	5.0	10.0		
209	210	3	30.0	90.0		
219	220	5	14.0	70.0		
222	223	1	30.0	30.0		
278	279	98	30.0	2940.0		
336	337	20	30.0	600.0		
363	364	20	30.0	600.0		
398	399	2	22.0	44.0		
412	413	5	30.0	150.0		
417	418	20	30.0	600.0		
508	509	30	30.0	900.0		
511	512	1	2.5	2.5		
519	520	20	30.0	600.0		
522	523	10	30.0	300.0		
529	530	4	30.0	120.0		

- Once you have created secondary variables such as USFREQMO and NUMCIGMO_EST you can then consider whether any of your quantitative variables or categorical variables need to be further grouped or binned.
- Currently AGE is a quantitative variable in the NESARC dataset, if we want to compare age groups categorically we need to group the values into categories.
- This would allow us to compare the number and percent of observations at each age group.

```
#quartile split qcut function into 4 groups

print('AGE - 4 Categories - quartiles')

subset2['AGEGROUP'] = pandas.qcut(subset2.AGE, 4,
labels=['1=25%tile','2=50%tile','3=75%tile','4=100%tile'])

c14= subset2['AGEGROUP'].value_counts(sort=False, dropna=True)

print(c14)
```

```
AGE - 4 Categories - quartiles

1=25%tile 582

2=50%tile 467

3=75%tile 231

4=100%tile 426

Name: AGEGROUP, dtype: int64

In [2]:
```

- Custom splits can also be set if you use the cut() function.
- This allows you to choose what every grouping you wish to use.
- The function can take several parameters (ref to pandas docs)
- In this example we pass the integer values that set up the bins.
- The first integer is one less than the first value in the bin (17 instead of 18)

```
#categorise variable based on customised splits using the cut()
functions

# splits into three groups, 18-20, 21-22, and 23-25

subset2['AGEGROUP2']= pandas.cut(subset2.AGE, [17, 20, 22, 25],
labels=['18-20','21-22','23-25'])

c15 = subset2['AGEGROUP2'].value_counts(sort=False, dropna=True)
print(c15)
```

```
18-20 582
21-22 467
23-25 657
Name: AGEGROUP2, dtype: int64
In [5]:
```

• We can now simply compare the two variables AGE and AGEGROUP2 in a crosstab.

```
print(pandas.crosstab(subset2['AGEGROUP2'], subset2['AGE']))
```

```
In [9]: print(pandas.crosstab(subset2['AGEGROUP2'],subset2['AGE']))

AGE 18 19 20 21 22 23 24 25

AGEGROUP2

18-20 161 200 221 0 0 0 0 0

21-22 0 0 0 239 228 0 0 0

23-25 0 0 0 0 0 231 241 185
```

The count of observations within each age group can be seen. This also serves as a check to make sure your grouping worked as expected.