# Project_4_Code

May 1, 2023

[82]:
```
#!pip install -r requirements.txt
```

[2]:
```
import pandas as pd
import cfe.regression as rgsn
```

```
Missing dependencies for OracleDemands.
```

### 0.0.1 data clean up

[3]:
```
Phillippines_Data = '1WmIn1GGsZKv9w96fug6fQAQH9GJwkatYMZRoBgB1GqY'
```

[4]:
```
InputFiles = {'Expenditures':(Phillippines_Data,'Expenditures'),
              'HH Characteristics':(Phillippines_Data,'HH Characteristics'),
              'FCT':(Phillippines_Data,'FCT'),
              'Quantities':(Phillippines_Data,'Quantities'),
             'Prices Per Household':(Phillippines_Data,'Prices Per Household')}
InputFiles
```

[4]:
```
{'Expenditures': ('1WmIn1GGsZKv9w96fug6fQAQH9GJwkatYMZRoBgB1GqY',
  'Expenditures'),
 'HH Characteristics': ('1WmIn1GGsZKv9w96fug6fQAQH9GJwkatYMZRoBgB1GqY',
  'HH Characteristics'),
 'FCT': ('1WmIn1GGsZKv9w96fug6fQAQH9GJwkatYMZRoBgB1GqY', 'FCT'),
 'Quantities': ('1WmIn1GGsZKv9w96fug6fQAQH9GJwkatYMZRoBgB1GqY', 'Quantities'),
 'Prices Per Household': ('1WmIn1GGsZKv9w96fug6fQAQH9GJwkatYMZRoBgB1GqY',
  'Prices Per Household')}
```

[5]:
```
from eep153_tools.sheets import read_sheets
import numpy as np
import pandas as pd
import warnings

def get_clean_sheet(key,sheet=None):

    df = read_sheets(key,sheet=sheet)
    df.columns = [c.strip() for c in df.columns.tolist()]

    df = df.loc[:,~df.columns.duplicated(keep='first')]
```

```
    df = df.drop([col for col in df.columns if col.startswith('Unnamed')],␣
 ↪axis=1)

    df = df.loc[~df.index.duplicated(), :]

    return df

# Get expenditures...
x = get_clean_sheet(InputFiles['Expenditures'][0],
                    sheet=InputFiles['Expenditures'][1])

if 'm' not in x.columns:
    x['m'] = 1

x = x.set_index(['i','t','m'])
x.columns.name = 'j'

x = x.apply(lambda x: pd.to_numeric(x,errors='coerce'))
x = x.replace(0,np.nan)

# Get HH characteristics...
z = get_clean_sheet(InputFiles['HH Characteristics'][0],
                    sheet=InputFiles['HH Characteristics'][1])

if 'm' not in z.columns:
    z['m'] = 1

z = z.set_index(['i','t','m'])
z.columns.name = 'k'

z = z.apply(lambda x: pd.to_numeric(x,errors='coerce'))

# Get prices
# Get prices
p = get_clean_sheet(InputFiles['Prices Per Household'][0],
                    sheet=InputFiles['Prices Per Household'][1])

if 'm' not in p.columns:  # Supply "market" indicator if missing
    p['m'] = 1

p = p.set_index(['t','i', 'm'])
p.columns.name = 'j'

p = p.apply(lambda x: pd.to_numeric(x,errors='coerce'))
p = p.replace(0,np.nan)
```

```
for i in p.columns:
    p[i] = p[i].median()

fct = get_clean_sheet(InputFiles['FCT'][0],
                    sheet=InputFiles['FCT'][1])

c = read_sheets(Phillippines_Data,sheet = 'Code Match ')
c.rename(columns ={'Code ' :'fct'}, inplace = True)
fct = fct.merge(c, how = 'inner', on = 'fct').drop(columns = ['Member', 'Food␣
 ↪', 'bouisfg', 'foodgrp'], axis = 1)
fct = fct.set_index('name')
fct.columns.name = 'n'

fct = fct.apply(lambda x: pd.to_numeric(x,errors='coerce'))

warnings.filterwarnings('default')
```

```
Key available for students@eep153.iam.gserviceaccount.com.
Key available for students@eep153.iam.gserviceaccount.com.
Key available for students@eep153.iam.gserviceaccount.com.
```

```
/opt/conda/lib/python3.9/site-packages/numpy/lib/nanfunctions.py:1117:
RuntimeWarning: Mean of empty slice
  return np.nanmean(a, axis, out=out, keepdims=keepdims)
/opt/conda/lib/python3.9/site-packages/numpy/lib/nanfunctions.py:1117:
RuntimeWarning: Mean of empty slice
  return np.nanmean(a, axis, out=out, keepdims=keepdims)
/opt/conda/lib/python3.9/site-packages/numpy/lib/nanfunctions.py:1117:
RuntimeWarning: Mean of empty slice
  return np.nanmean(a, axis, out=out, keepdims=keepdims)
/opt/conda/lib/python3.9/site-packages/numpy/lib/nanfunctions.py:1117:
RuntimeWarning: Mean of empty slice
  return np.nanmean(a, axis, out=out, keepdims=keepdims)
```

```
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```

Here, use data on log *expenditures* and household characteristics to create a CFEDemand `result`.

[6]:
```
import cfe
import numpy as np

result = cfe.Regression(y=np.log(x.stack()),d=z)

result.to_pickle('phillippines_estimates.pickle')
result = cfe.read_pickle('phillippines_estimates.pickle')  # Get persistent␣
 ↪result saved above...
```

[7]:
```
%matplotlib notebook

x_1d = x.groupby('j',axis=1).sum()
x_1d = x_1d.replace(0,np.nan) # Replace zeros with missing

y = np.log(x_1d)

from cfe.estimation import drop_columns_wo_covariance
y = drop_columns_wo_covariance(y,min_obs=30)

y = y.stack()
```

[8]:
```
import cfe

xhat = result.predicted_expenditures()

# Expenditures divided by prices/kg gives quantities in kgs...
qhat = (xhat.unstack('j')/p).dropna(how='all')

# Drop missing columns
qhat = qhat.loc[:,qhat.count()>0]
```

### 0.0.2 Manually reduced the food items to match the FCT code

[9]:
```
# translate qhat names to match fct names
translate = get_clean_sheet(Phillippines_Data, sheet='Code Match ')

translate = translate.drop(['Member', ''], axis=1)

translate = translate[translate['Food'].isin(list(qhat.columns))]

fct_names = fct[fct['fct'].isin(list(translate['Code']))].
↪reset_index()[['name', 'fct']]

translate_names = translate.merge(fct_names, left_on='Code', right_on='fct')
names_dict = dict(zip(list(translate_names['Food']),␣
↪list(translate_names['name'])))

qhat_fct = qhat.rename(columns=names_dict)
```

```
Key available for students@eep153.iam.gserviceaccount.com.
```

```
/tmp/ipykernel_29/2540959960.py:8: ResourceWarning: unclosed <ssl.SSLSocket
fd=56, family=AddressFamily.AF_INET, type=SocketKind.SOCK_STREAM, proto=6,
laddr=('10.20.2.154', 46698), raddr=('74.125.124.95', 443)>
  df = read_sheets(key,sheet=sheet)
ResourceWarning: Enable tracemalloc to get the object allocation traceback
```

[10]:
```python
# select relevant data and remove duplicates
use = fct.index.intersection(qhat_fct.columns)

fct = fct[~fct.index.duplicated(keep='first')].loc[use]
qhat_fct = qhat_fct.loc[:,~qhat_fct.columns.duplicated(keep='first')][use]
qhat_fct
```

[10]:
```
j                        Rice milled, white  Corn, yellow  Mango, ripe
i     t      m
2.0   2003.0 Bukidnon          17053.503971     74.643002   999.023488  \
4.0   2003.0 Bukidnon          17014.186862    396.164203   411.124682
5.0   2003.0 Bukidnon           6541.938988    126.248867   260.014014
6.0   2003.0 Bukidnon          17659.517960    273.488517   550.780633
12.0  2003.0 Bukidnon          12252.715179    393.643043   471.738985
…                                         …             …            …
937.0 2003.0 Bukidnon          10199.694209    385.334146   681.199834
938.0 2003.0 Bukidnon          12351.640527    290.859517   535.023577
939.0 2003.0 Bukidnon           6159.018422     31.018894   138.877190
940.0 2003.0 Bukidnon          10523.450572    226.678506   447.365593
941.0 2003.0 Bukidnon          11200.727057    241.307127  1264.122567

j                             Banana  Bitter melon, boiled  Squash fruit
i     t      m
2.0   2003.0 Bukidnon  1430.789141            391.342640    646.725219  \
4.0   2003.0 Bukidnon   976.171927            650.923721   1034.043102
5.0   2003.0 Bukidnon   333.973326            262.913068    395.645334
6.0   2003.0 Bukidnon  1183.863641            993.000677   1188.437543
12.0  2003.0 Bukidnon   853.221166            559.787756    999.261822
…                              …                     …             …
937.0 2003.0 Bukidnon   735.160679            574.006046    648.272206
938.0 2003.0 Bukidnon   836.705188            526.294259    817.328327
939.0 2003.0 Bukidnon   107.884131             71.912630    120.018549
940.0 2003.0 Bukidnon  1019.835278            636.650217    840.193621
941.0 2003.0 Bukidnon  1231.614101            810.167251   1132.043492

j                             Tomato  Sweet potato, yellow      Carrot
i     t      m
2.0   2003.0 Bukidnon   455.588058            957.764679  623.985324  \
4.0   2003.0 Bukidnon   554.505987           2419.182014  589.675182
5.0   2003.0 Bukidnon   179.602497            777.019740  198.521297
6.0   2003.0 Bukidnon  1011.190959           1664.512741  749.145368
12.0  2003.0 Bukidnon   410.113476           1663.038430  343.555921
…                              …                     …           …
937.0 2003.0 Bukidnon   359.857046           1017.945685  410.715123
938.0 2003.0 Bukidnon   373.385477           1304.015045  363.737175
939.0 2003.0 Bukidnon    75.030844            211.001450  117.613744
940.0 2003.0 Bukidnon   486.419206           1029.048109  458.638766
```

```
941.0 2003.0 Bukidnon   572.956694          1272.525647  322.301425

j                         Seaweed  …  Sardines canned in oil
i     t      m                     …
2.0   2003.0 Bukidnon  141.843666  …              326.815415  \
4.0   2003.0 Bukidnon  594.426008  …              462.140288
5.0   2003.0 Bukidnon  184.152011  …              129.577533
6.0   2003.0 Bukidnon  629.391888  …              621.406239
12.0  2003.0 Bukidnon  576.337380  …              425.619234
…                              …  …                    …
937.0 2003.0 Bukidnon  463.825026  …              239.385285
938.0 2003.0 Bukidnon  397.633502  …              304.859049
939.0 2003.0 Bukidnon   27.506125  …               94.399510
940.0 2003.0 Bukidnon  372.891248  …              366.898362
941.0 2003.0 Bukidnon  520.045238  …              339.515493

j                      Sugar white, refined  "Kalamansi" nectar    Corn oil
i     t      m
2.0   2003.0 Bukidnon           1112.454402          862.442278  650.263995  \
4.0   2003.0 Bukidnon           1188.685532          319.192357  644.791984
5.0   2003.0 Bukidnon            535.389724          120.952965  261.567133
6.0   2003.0 Bukidnon           1487.143600         1060.863807  787.224508
12.0  2003.0 Bukidnon           1350.597614          248.885674  588.797634
…                                         …                 …           …
937.0 2003.0 Bukidnon            905.185076          320.236474  419.938814
938.0 2003.0 Bukidnon           1021.956322          360.445268  429.392836
939.0 2003.0 Bukidnon            355.789979           93.620767  103.465091
940.0 2003.0 Bukidnon           1086.279566          513.824837  643.770388
941.0 2003.0 Bukidnon           1051.893679          451.946636  676.481804

j                      Soluble coffee  Fish sauce  Coconut vinegar
i     t      m
2.0   2003.0 Bukidnon       20.397007  221.473400        23.398519  \
4.0   2003.0 Bukidnon       38.204560  401.998251        29.270211
5.0   2003.0 Bukidnon       12.075665  151.573752        12.139638
6.0   2003.0 Bukidnon       33.117341  538.745561        37.323828
12.0  2003.0 Bukidnon       24.256634  343.290073        39.275725
…                                   …           …                …
937.0 2003.0 Bukidnon       17.934228  226.665787        16.827990
938.0 2003.0 Bukidnon       24.267126  272.780222        18.507985
939.0 2003.0 Bukidnon        4.417256   90.043398         7.190814
940.0 2003.0 Bukidnon       24.932869  306.928896        18.475353
941.0 2003.0 Bukidnon       32.462168  261.251487        22.507528

j                            Milo   Softdrinks         Beer
i     t      m
2.0   2003.0 Bukidnon   95.259586  1361.231553   467.589378
```

```
4.0   2003.0 Bukidnon  112.367171  2035.635537   991.796732
5.0   2003.0 Bukidnon   50.610025   824.842370   654.024659
6.0   2003.0 Bukidnon  120.379875  2751.345840  2451.334919
12.0  2003.0 Bukidnon  166.842770  2243.083523  3590.344832
…                               …            …            …
937.0 2003.0 Bukidnon  112.710016  1308.016138   885.371474
938.0 2003.0 Bukidnon  117.180304  1598.336104   843.847054
939.0 2003.0 Bukidnon   16.647666   373.032112   198.912647
940.0 2003.0 Bukidnon  127.624680  2038.015652  1105.048534
941.0 2003.0 Bukidnon  138.254970  2129.899520  1008.321478

[569 rows x 40 columns]
```

### 0.0.3 General overview of the nutritional consumption is for the household

[11]:
```
# calculate the calorie consumption per household by type of food consumed
consumption_calories = qhat_fct[use]
for col in consumption_calories.columns:
    consumption_calories[col] = consumption_calories[col] * fct['calorie'].
 ↪loc[col]
consumption_calories
```

[11]:
```
j                      Rice milled, white  Corn, yellow   Mango, ripe
i     t      m
2.0   2003.0 Bukidnon        6.258636e+06  12465.381292  62938.479715  \
4.0   2003.0 Bukidnon        6.244207e+06  66159.421871  25900.854960
5.0   2003.0 Bukidnon        2.400892e+06  21083.560737  16380.882862
6.0   2003.0 Bukidnon        6.481043e+06  45672.582351  34699.179859
12.0  2003.0 Bukidnon        4.496746e+06  65738.388238  29719.556070
…                                     …             …             …
937.0 2003.0 Bukidnon        3.743288e+06  64350.802318  42915.589515
938.0 2003.0 Bukidnon        4.533052e+06  48573.539349  33706.485329
939.0 2003.0 Bukidnon        2.260360e+06   5180.155340   8749.262984
940.0 2003.0 Bukidnon        3.862106e+06  37855.310521  28184.032352
941.0 2003.0 Bukidnon        4.110667e+06  40298.290137  79639.721735

j                             Banana  Bitter melon, boiled  Squash fruit
i     t      m
2.0   2003.0 Bukidnon  135924.968403           6261.482246  24575.558326  \
4.0   2003.0 Bukidnon   92736.333091          10414.779538  39293.637859
5.0   2003.0 Bukidnon   31727.465971           4206.609081  15034.522677
6.0   2003.0 Bukidnon  112467.045860          15888.010830  45160.626622
12.0  2003.0 Bukidnon   81056.010795           8956.604089  37971.949237
…                                  …                     …             …
937.0 2003.0 Bukidnon   69840.264519           9184.096738  24634.343818
938.0 2003.0 Bukidnon   79486.992907           8420.708136  31058.476427
939.0 2003.0 Bukidnon   10248.992419           1150.602083   4560.704843
```

```
940.0 2003.0 Bukidnon   96884.351422          10186.403468  31927.357590
941.0 2003.0 Bukidnon  117003.339635          12962.676015  43017.652692

j                            Tomato  Sweet potato, yellow        Carrot
i     t      m
2.0   2003.0 Bukidnon  10478.525324         129298.231637  29951.295567  \
4.0   2003.0 Bukidnon  12753.637703         326589.571857  28304.408749
5.0   2003.0 Bukidnon   4130.857422         104897.664895   9529.022261
6.0   2003.0 Bukidnon  23257.392052         224709.220058  35958.977640
12.0  2003.0 Bukidnon   9432.609957         224510.188026  16490.684208
…                               …                    …             …
937.0 2003.0 Bukidnon   8276.712057         137422.667504  19714.325917
938.0 2003.0 Bukidnon   8587.865982         176042.031139  17459.384407
939.0 2003.0 Bukidnon   1725.709420          28485.195814   5645.459694
940.0 2003.0 Bukidnon  11187.641731         138921.494732  22014.660790
941.0 2003.0 Bukidnon  13178.003966         171790.962360  15470.468401

j                            Seaweed  …  Sardines canned in oil
i     t      m                        …
2.0   2003.0 Bukidnon   28226.889471  …            66343.529314  \
4.0   2003.0 Bukidnon  118290.775579  …            93814.478557
5.0   2003.0 Bukidnon   36646.250239  …            26304.239163
6.0   2003.0 Bukidnon  125248.985632  …           126145.466563
12.0  2003.0 Bukidnon  114691.138593  …            86400.704461
…                                …  …                       …
937.0 2003.0 Bukidnon   92301.180178  …            48595.212897
938.0 2003.0 Bukidnon   79129.066816  …            61886.387041
939.0 2003.0 Bukidnon    5473.718814  …            19163.100540
940.0 2003.0 Bukidnon   74205.358374  …            74480.367420
941.0 2003.0 Bukidnon  103489.002372  …            68921.645087

j                      Sugar white, refined  "Kalamansi" nectar
i     t      m
2.0   2003.0 Bukidnon         430519.853587       129366.341689  \
4.0   2003.0 Bukidnon         460021.300959        47878.853525
5.0   2003.0 Bukidnon         207195.823306        18142.944683
6.0   2003.0 Bukidnon         575524.573302       159129.571087
12.0  2003.0 Bukidnon         522681.276546        37332.851044
…                                       …                   …
937.0 2003.0 Bukidnon         350306.624304        48035.471042
938.0 2003.0 Bukidnon         395497.096545        54066.790264
939.0 2003.0 Bukidnon         137690.721842        14043.115020
940.0 2003.0 Bukidnon         420390.192135        77073.725483
941.0 2003.0 Bukidnon         407082.853852        67791.995439

j                           Corn oil  Soluble coffee    Fish sauce
i     t      m
```

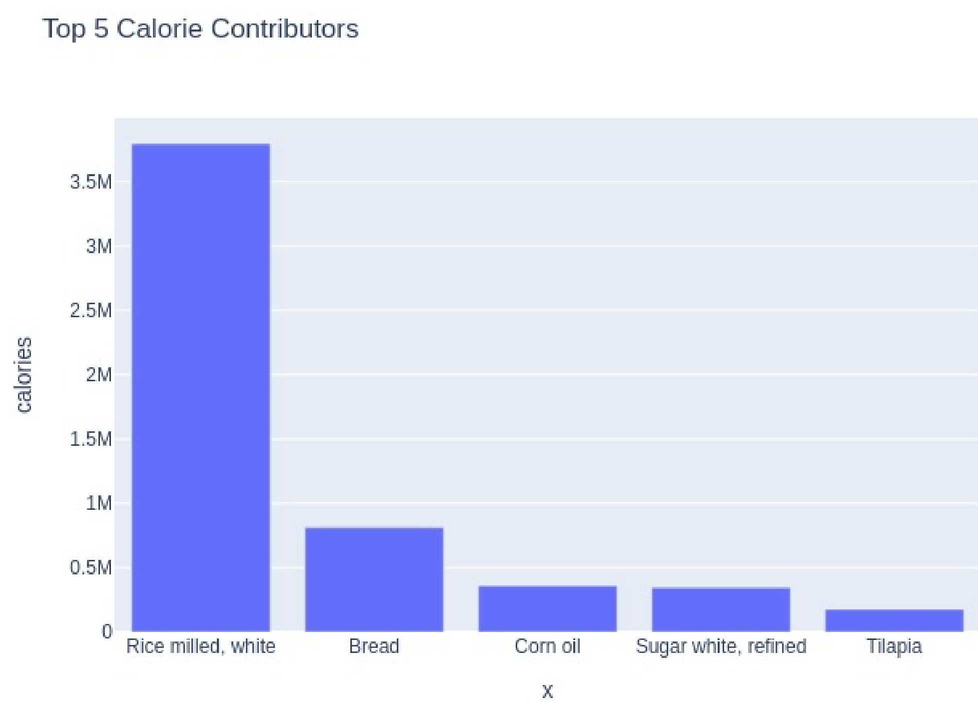
```
2.0   2003.0 Bukidnon  572232.315947    7281.731363  10852.196614  \
4.0   2003.0 Bukidnon  567416.945669   13639.027985  19697.914309
5.0   2003.0 Bukidnon  230179.076630    4311.012462   7427.113827
6.0   2003.0 Bukidnon  692757.567326   11822.890651  26398.532477
12.0  2003.0 Bukidnon  518141.917974    8659.618510  16821.213578
…                                …              …             …
937.0 2003.0 Bukidnon  369546.156031    6402.519291  11106.623587
938.0 2003.0 Bukidnon  377865.695867    8663.364004  13366.230889
939.0 2003.0 Bukidnon   91049.279730    1576.960454   4412.126510
940.0 2003.0 Bukidnon  566517.941425    8901.034363  15039.515881
941.0 2003.0 Bukidnon  595303.987448   11588.993944  12801.322844

j                      Coconut vinegar          Milo     Softdrinks
i     t      m
2.0   2003.0 Bukidnon        70.195558  37722.796061   53088.030582  \
4.0   2003.0 Bukidnon        87.810634  44497.399826   79389.785934
5.0   2003.0 Bukidnon        36.418914  20041.569720   32168.852424
6.0   2003.0 Bukidnon       111.971485  47670.430426  107302.487774
12.0  2003.0 Bukidnon       117.827175  66069.736723   87480.257395
…                                  …             …              …
937.0 2003.0 Bukidnon        50.483969  44633.166282   51012.629389
938.0 2003.0 Bukidnon        55.523955  46403.400387   62335.108051
939.0 2003.0 Bukidnon        21.572443   6592.475758   14548.252364
940.0 2003.0 Bukidnon        55.426058  50539.373252   79482.610421
941.0 2003.0 Bukidnon        67.522584  54748.968266   83066.081263

j                               Beer
i     t      m
2.0   2003.0 Bukidnon   19638.753860
4.0   2003.0 Bukidnon   41655.462727
5.0   2003.0 Bukidnon   27469.035661
6.0   2003.0 Bukidnon  102956.066585
12.0  2003.0 Bukidnon  150794.482944
…                                …
937.0 2003.0 Bukidnon   37185.601903
938.0 2003.0 Bukidnon   35441.576287
939.0 2003.0 Bukidnon    8354.331179
940.0 2003.0 Bukidnon   46412.038425
941.0 2003.0 Bukidnon   42349.502070

[569 rows x 40 columns]
```

[12]:

```python
#import seaborn as sns
import plotly.express as px

top5_calorie = pd.DataFrame({'calories': consumption_calories.mean()}).
 ↪sort_values(by='calories', ascending=False).head(5)
```

```
cal_cont = px.bar(top5_calorie, x=list(top5_calorie.index),␣
 ↪y=top5_calorie['calories'], title='Top 5 Calorie Contributors')
cal_cont.show('jpg')
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```




# 1 Demands

[13]:
```
result.beta.index
```

[13]:
```
Index(['Alcoholic drinks', 'Ampalaya', 'Atsal', 'Bagoong', 'Banana', 'Beef',
       'Calamansi', 'Carrots', 'Chicken', 'Coffee', 'Coke', 'Cooking oil',
       'Corn products', 'Dried fish and smoked fish', 'Eggs',
       'Food made from flour', 'Fresh fish', 'Mangoes', 'Milk', 'Milo',
       'Mongo and other products', 'Okra', 'Onions', 'Petsay', 'Pork',
       'Potato', 'Processed meat like longanisa', 'Rice', 'Rice products',
       'Salt', 'Sardines like youngstown, etc', 'Sea weed', 'Sitao',
```

```
        'Snaks like chippy, cheese curls, bread sticks',
        'Soybean and other products', 'Squash', 'Sugar', 'Sweet potato',
        'Talong', 'Tomatoes', 'Vetsin, MSG', 'Vinegar'],
       dtype='object', name='j')
```

[14]:
```
# Reference prices chosen from a particular time; average across place.
# These are prices per kilogram:
pbar = p.mean()
pbar = pbar[result.beta.index]
```

[15]:
```
import numpy as np

xhat = result.predicted_expenditures()

# Total food expenditures per household
xbar = xhat.groupby(['i','t','m']).sum()

# Reference budget
xref = xbar.quantile(0.5)  # Household at 0.5 quantile is median
```

#### 1.0.1 The following codes are used to estimate a system of demands for different kinds of food by defining 'use' as a food of interest and describe demands as function of prices.

[16]:
```
def my_prices(p0,p=pbar,j='Rice'):
    """
    Change price of jth good to p0, holding other prices fixed.
    """
    p = p.copy()
    p.loc[j] = p0
    return p
```

[17]:
```
result.demands(xref,pbar)
```

[17]:
```
j
Alcoholic drinks                                    106.026147
Ampalaya                                            602.509123
Atsal                                              1034.941413
Bagoong                                              33.060910
Banana                                             1903.304612
Beef                                                180.324567
Calamansi                                          2864.990954
Carrots                                             280.704003
Chicken                                             413.172772
Coffee                                               77.865798
Coke                                                544.017436
Cooking oil                                         399.832003
```

```
Corn products                                         122.882550
Dried fish and smoked fish                             57.001429
Eggs                                                  732.269398
Food made from flour                                  294.363426
Fresh fish                                           1136.937918
Mangoes                                                75.731435
Milk                                                  378.061363
Milo                                                  191.036006
Mongo and other products                              209.570176
Okra                                                  340.120745
Onions                                                848.237574
Petsay                                               3689.200940
Pork                                                  245.409799
Potato                                                 20.882765
Processed meat like longanisa                         283.625880
Rice                                                   14.603808
Rice products                                         149.500811
Salt                                                   49.720437
Sardines like youngstown, etc                         239.538062
Sea weed                                              605.106494
Sitao                                                1010.374726
Snaks like chippy, cheese curls, bread sticks         207.960059
Soybean and other products                            203.107459
Squash                                                493.030094
Sugar                                                  38.973450
Sweet potato                                           36.829837
Talong                                               1812.408275
Tomatoes                                              866.765775
Vetsin, MSG                                            85.860276
Vinegar                                                19.813170
Name: quantities, dtype: float64
```

[18]:
```
# To see the demnads of each food item
import plotly.express as px
import pandas as pd
%matplotlib notebook
demand_df = pd.DataFrame({'demand': result.demands(xref,pbar)})
px.bar(demand_df,x=list(result.demands(xref,pbar).index),
  ↪y=demand_df['demand'], title='Demand for each food product', labels={"x" :
  ↪'food items'})
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```

[19]:
```python
# To see the relative changes in price with varying quantities in demand we can␣
↪redefine 'use' to food items of interest.
import matplotlib.pyplot as plt

%matplotlib notebook

use = 'Talong'

# Vary prices from 50% to 200% of reference.
scale = np.linspace(.5,2,20)

# Demand for Talong for household at median budget
plt.plot([result.demands(xref,my_prices(pbar[use]*s,pbar,use))[use] for s in␣
↪scale],scale, color = 'blue', label = 'median budget')

# Demand for Talong for household at 25% percentile denoted in red
plt.plot([result.demands(xbar.quantile(0.
↪25),my_prices(pbar[use]*s,pbar,use))[use] for s in scale],scale,color =␣
↪'red', label = '25% percentile')

# Demand for Talong for household at 75% percentile
plt.plot([result.demands(xbar.quantile(0.
↪75),my_prices(pbar[use]*s,pbar,use))[use] for s in scale],scale, color =␣
↪'green', label = '75% percentile')

plt.ylabel(f"Price (relative to base of {pbar[use]:.2f})")
plt.xlabel(f"Quantities of {use} Demanded (Kgs)")
plt.legend()
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

[19]:
```
<matplotlib.legend.Legend at 0x7f236d7a2e20>
```

The visualization represents how household expenditure on a particular goods and services varies with household income.

[20]:
```python
import matplotlib.pyplot as plt
import numpy as np

%matplotlib notebook

fig,ax = plt.subplots()

scale = np.geomspace(.01,10,50)
```

```
ax.plot(np.log(scale*xref),[result.expenditures(s*xref,pbar)/(s*xref) for s in␣
 ↪scale])
ax.set_xlabel(f'log budget (relative to base of {xref:.0f})')
ax.set_ylabel(f'Expenditure share')
ax.set_title('Engel Curves')
ax.legend([result.expenditures(s*xref,pbar)/(s*xref) for s in scale][0].index.
 ↪tolist(), loc = 'best', bbox_to_anchor = (0.8,0.2), bbox_transform = fig.
 ↪transFigure)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

[20]:
```
<matplotlib.legend.Legend at 0x7f236d784280>
```

### 1.0.2 To look more closely at how the demand in quantities change as a code describes the quantities demanded as function of budgets to analyze the quntities into nutrients.

[21]:
```
# Create a new FCT and vector of consumption that only share rows in common:
fct0,c0 = fct.align(qhat.T,axis=0,join='inner')
print(fct0.index)
```

```
Index(['Banana', 'Okra', 'Milo'], dtype='object')
```

[22]:
```
# The @ operator means matrix multiply
# N describes how much each household consumes each category of nutrients in a␣
 ↪week.
N = fct0.T@c0

N
```

[22]:
```
i                   2.0            4.0            5.0            6.0
t                2003.0         2003.0         2003.0         2003.0
m              Bukidnon       Bukidnon       Bukidnon       Bukidnon
n
fct       445931.461860  610158.045361  171611.808380  546477.952375  \
calorie   189384.716147  170926.572032   58269.943301  184720.045118
protein     2886.002008    3496.490619    1008.299202    3272.281796
fat         1099.339742    1106.701286     401.965113    1168.895948
carbo      46781.042886   41247.654105   13982.472456   44909.629610
fiber        860.764369    1180.119425     282.958698    1017.875263
ash         1747.626194    1870.466296     541.043405    1826.490858
calcium    82799.232411  138292.282741   30777.654625  110787.570978
phos      104499.915521  115597.982404   33861.078855  111927.881706
iron        1280.285617    1532.667850     420.607397    1423.179816
retinol     2190.970478    2584.444939    1164.030565    2768.737121
carotene  149778.714674  195447.474539   46448.336729  170898.504322
```

```
thiamine       96.400173     125.461678      34.361940     113.366254
riboflav       99.412779     133.743346      35.381273     118.640709
niacin       1595.021321    1761.612387     502.585070    1696.066506
ascorbic    39926.716843   43740.166659   11351.993865   41345.994161
edpor      149649.007660  171401.346265   45721.017952  160495.326246
blufct               NaN            NaN            NaN            NaN
                     NaN            NaN            NaN            NaN

i                   12.0           13.0           14.0           15.0
t                 2003.0         2003.0         2003.0         2003.0
m               Bukidnon       Bukidnon       Bukidnon       Bukidnon
n
fct        378737.573609  252110.922734  169739.328854  400118.154025  \
calorie    153407.100391   78371.169120   64191.649875  135671.504392
protein      2271.396039    1456.154399    1029.990515    2283.523126
fat          1131.339385     538.373350     428.662109    1044.778143
carbo       36521.432556   18784.232132   15513.575466   31947.191278
fiber         479.737280     437.154830     278.030599     541.766368
ash          1206.664848     771.902036     572.308906    1150.753990
calcium     45421.098100   49549.023998   28404.359567   59143.838580
phos        77054.358151   48293.191055   35465.505013   74486.723206
iron          883.961390     615.579809     431.083723     893.465542
retinol      3837.383699    1506.029738    1195.384478    3656.463076
carotene    76711.266022   71661.379071   46318.057548   84967.219111
thiamine       72.705648      50.681804      34.408710      76.056928
riboflav       71.331716      52.882621      35.079313      76.433369
niacin       1104.658454     721.977279     526.966286    1070.290396
ascorbic    21579.145703   16749.297694   11962.214854   21091.925895
edpor       91516.400045   67204.080421   47485.281255   91160.603633
blufct               NaN            NaN            NaN            NaN
                     NaN            NaN            NaN            NaN

i                   16.0           17.0  …           931.0          932.0
t                 2003.0         2003.0  …          2003.0         2003.0
m               Bukidnon       Bukidnon  …        Bukidnon       Bukidnon
n                                        …
fct        622004.676374  301196.313284  …   407446.368603  218450.033039  \
calorie    168250.185958  106781.392489  …   135256.372383   77081.340296
protein      3547.131477    1849.656268  …     2381.997560    1275.879567
fat          1079.126980     632.992014  …      934.051707     561.564674
carbo       40624.485473   26223.099481  …    32435.856589   18343.747302
fiber        1227.176388     597.499165  …      678.835280     320.085694
ash          1893.670970    1070.062854  …     1272.769749     668.692118
calcium    145252.119003   63585.193681  …    74694.724822   34055.630650
phos       116876.258610   64600.608757  …    79693.814706   42511.632767
iron         1565.166095     823.672183  …      996.048117     513.201753
retinol      2414.725171    1256.460982  …     2693.673714    1815.426844
```

```
carotene  203336.051717  101962.965449  …  111318.494359   51530.285752
thiamine     128.282333      64.101658  …      81.595707      42.580184
riboflav     137.415966      67.397940  …      84.279803      43.058994
niacin      1787.668947     989.753588  …    1184.433080     619.493050
ascorbic   44937.449627   25063.647593  …   26885.776237   12993.297328
edpor     175586.506453   95109.662017  …  108288.189911   54085.093114
blufct              NaN            NaN  …            NaN            NaN
                    NaN            NaN  …            NaN            NaN

i                 933.0          935.0          936.0          937.0
t                2003.0         2003.0         2003.0         2003.0
m              Bukidnon       Bukidnon       Bukidnon       Bukidnon
n
fct       614245.128301  533431.913065  591573.273489  410385.969212  \
calorie   229099.731296  208411.663851  196447.527878  131700.165011
protein     3720.078528    3242.225027    3472.257649    2382.946037
fat         1521.844801    1424.486585    1334.458205     908.926432
carbo      55399.196306   50213.774227   47234.178967   31564.199272
fiber       1022.512228     822.170209    1009.541295     696.300565
ash         2067.333810    1790.244325    1870.584865    1266.758933
calcium   105444.422955   81851.536624  111001.064566   77854.780682
phos      127957.760061  111610.877146  116622.592276   79326.224910
iron        1564.037222    1333.546352    1463.936525    1001.126723
retinol     4180.465160    4199.072670    3719.837426    2592.330365
carotene  170491.110717  136123.362834  166361.208214  114093.248478
thiamine     124.842524     106.859558     119.295097      82.280305
riboflav     127.697532     107.776594     123.596618      85.409459
niacin      1905.626926    1644.097280    1740.426487    1181.971864
ascorbic   43633.639383   36085.368284   40130.206799   27084.928797
edpor     172753.430586  145058.903265  160368.728684  108976.957056
blufct              NaN            NaN            NaN            NaN
                    NaN            NaN            NaN            NaN

i                 938.0         939.0          940.0          941.0
t                2003.0        2003.0         2003.0         2003.0
m              Bukidnon      Bukidnon       Bukidnon       Bukidnon
n
fct       410770.452173  84266.689300  469699.466411  491590.386816
calorie   141569.097671  21625.569884  165510.050613  188437.438019
protein     2431.308335    470.249363    2810.231763    3016.668946
fat          959.985346    147.968785    1095.284708    1219.075070
carbo      34073.585316   5162.871571   40003.762514   45770.828809
fiber        689.851288    158.626848     809.158604     841.914472
ash         1319.128429    242.534713    1548.800667    1706.580469
calcium    74430.827858  19187.003338   86274.215344   85494.513599
phos       82171.097997  15185.345227   95849.829546  104870.920999
iron        1021.244751    203.510407    1191.800211    1281.794250
```

```
retinol       2695.146992    382.896319    2935.367638    3179.864318
carotene    113897.047843  25908.461027  134665.815818  141680.187193
thiamine        82.834382     17.031280      95.683832     101.098139
riboflav        85.390371     18.193358      98.783316     103.547143
niacin        1223.739880    230.081533    1434.054671    1569.593562
ascorbic     28003.172541   5596.255716   33396.252332   36624.719301
edpor       111873.634091  22348.289414  131959.223333  143270.570291
blufct                NaN           NaN            NaN            NaN
                      NaN           NaN            NaN            NaN

[19 rows x 569 columns]
```

[23]:

```python
#N describes nutrient demand based on consumption defined b c and multiplying␣
↪it by fct of each food category
def nutrient_demand(x,p):
    c = result.demands(x,p)
    fct0,c0 = fct.align(c,axis=0,join='inner')
    N = fct0.T@c0

    N = N.loc[~N.index.duplicated()]

    return N
```

**The graph here represents the variation of nutrient outcomes with budget with fixed price.**

[24]:

```python
import numpy as np
import matplotlib.pyplot as plt
%matplotlib notebook
X = np.linspace(xref/5,xref*5,50)

UseNutrients = fct.columns.tolist()

df = pd.concat({myx:np.log(nutrient_demand(myx,pbar))[UseNutrients] for myx in␣
↪X},axis=1).T
ax = df.plot()
ax.set_xlabel('Budget')
ax.set_ylabel('log nutrient')
ax.set_title("Demand for nutrients by Household")
```

```
<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>
```

[24]:

```
Text(0.5, 1.0, 'Demand for nutrients by Household')
```

**The visualization shows the varition of nutrition in respect to the prices.**

[25]:
```
USE_GOOD = 'Fresh fish'

scale = np.geomspace(.01,10,50)

ndf = pd.DataFrame({s:np.log(nutrient_demand(xref/
  ↪2,my_prices(pbar[USE_GOOD]*s,j=USE_GOOD)))[UseNutrients] for s in scale}).T

ax = ndf.plot()

ax.set_xlabel('log price')
ax.set_ylabel('log nutrient')
ax.set_title("Demand for Nutrients by Price of %s" % USE_GOOD)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

[25]:
```
Text(0.5, 1.0, 'Demand for Nutrients by Price of Fresh fish')
```

The above graph makes sense because the nutrient each food have may vary a little, but it should not have great changes depending on the price as should not be a factor that affects nutrients.

### 1.0.3 Nutritional Needs of Households

Considering that our data on demand and nutrients are at household level, we cannot make comparisons to individual level requirement. Therefore, we set up minimum individual requirements to see the household total exceed these. This minimum individual requriement will tell us if all individuals in the household have adequate nutrition.

The rdi defined in our data is categorized by gender and age. This will tell us whether or not

[60]:
```
rdi = get_clean_sheet(Phillippines_Data,
                      sheet='RDI')
```

```
Key available for students@eep153.iam.gserviceaccount.com.
```

```
/tmp/ipykernel_29/2540959960.py:8: ResourceWarning:

unclosed <ssl.SSLSocket fd=67, family=AddressFamily.AF_INET,
type=SocketKind.SOCK_STREAM, proto=6, laddr=('10.20.2.154', 51158),
raddr=('74.125.201.95', 443)>
```

[61]:
```
rdi = rdi.drop(columns = 'units')
rdi = rdi.set_index('n')
```

In our regression model, d equates to each individual's gender and age range of individual households. The defined dbar below is the average composition of housholds over the given data by gender and age range

[28]:
```
#average composition of households by gender and age range
dbar = result.d.mean().iloc[:-2]
```

[29]:
```
dbar
```

[29]:
```
k
Males 0-1          0.094903
Males 1-5          0.277680
Males 5-10         0.256591
Males 10-15        0.325132
Males 15-20        0.363796
Males 20-30        0.975395
Males 30-50        0.862917
Males 50-60        0.209139
Males 60-100       0.163445
Females 0-1        0.072056
Females 1-5        0.233743
Females 5-10       0.286467
Females 10-15      0.307557
Females 15-20      0.369069
Females 20-30      0.810193
Females 30-50      0.806678
Females 50-60      0.223199
Females 60-100     0.135325
dtype: float64
```

[30]:
```
# This matrix product gives minimum nutrient requirements for the average␣
↪household
hh_rdi = rdi.replace('',0)@dbar

hh_rdi
```

[30]:
```
n
calorie     13954.253076
protein       381.050967
fat           462.061511
carbo         880.527241
fiber         139.216169
calcium      5701.889279
phos         5210.500879
iron          114.673111
retinol      2879.142355
thiamine        5.783831
riboflav        6.171353
niacin         71.439367
ascorbic      325.641476
dtype: float64
```

[31]:
```
# fiding the average nutritional content for each household
use = fct.index.intersection(qhat_fct.columns)
fct = fct.fillna(0)
nutrients = qhat_fct[use]@fct.loc[use,:]
nutrients = nutrients.drop(columns =
 ↪['fct','edpor','blufct','ash','carotene','']) #dropped columns with
 ↪insufficient data
avg_nutrients = nutrients.mean()/365 # NB: Nutrients are by year
avg_nutrients
```

[31]:
```
n
calorie     19115.069974
protein       686.953242
fat           288.430691
carbo        3376.064550
fiber          39.247315
calcium      4671.093000
phos         9214.243910
iron          138.599359
retinol      2773.631385
thiamine        7.010399
riboflav        7.655856
niacin        189.389227
ascorbic      509.363407
dtype: float64
```

[32]:
```
#rdi diff - household minimum nutrient requirements on average - actual
 ↪nutrient consumed on average
#allows us to see which category they are deficient in general.
rdi_diff = hh_rdi - avg_nutrients
rdi_diff
```

[32]:
```
n
calorie    -5160.816898
protein     -305.902276
fat          173.630821
carbo      -2495.537309
fiber         99.968853
calcium     1030.796280
phos       -4003.743032
iron         -23.926248
retinol      105.510970
thiamine      -1.226568
riboflav      -1.484502
niacin      -117.949860
ascorbic    -183.721931
dtype: float64
```

### 1.0.4 Nutritional Adequacy of Food Demands

[62]:
```
def nutrient_adequacy_ratio(x,p,d,rdi=rdi,days=7):
    hh_rdi = rdi.replace('',0)@d*days

    return nutrient_demand(x,p)/hh_rdi
```

hh_rdi in the function above represents the recommended dietary intake per household based on composition of each household based on gender and age. Recall that N, defined by nutrient demand function, describes individual household consumption for each food category. Therefore, the nutreint adequacy ratio will be the ratio of actual nutrient intake to recommended nutrient intake.

This information is useful because it normalizes the nutritional intake to check the adequacy of the diet per household with counts of different kinds of people defined in z, the household characteristics by gender and age range.

[63]:
```
X = np.geomspace(.01*xref,2*xref,100)
UseNutrients = fct.columns.tolist()
pd.DataFrame({x:np.log(nutrient_adequacy_ratio(x,pbar,dbar))[UseNutrients] for␣
↪x in X}).T.plot()
plt.legend(UseNutrients)
plt.xlabel('budget')
plt.ylabel('log nutrient adequacy ratio')
plt.axhline(0)
plt.axvline(xref)
plt.title("Nutrient Adequacy Ratio by household budget")
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

[63]:
```
Text(0.5, 1.0, 'Nutrient Adequacy Ratio by household budget')
```

We can also vary relative prices. Here we trace out nutritional adequacy varying the price of a single good.

[64]:
```
scale = np.geomspace(.01,2,50)

USE_GOOD = 'Fresh fish'

ndf = pd.DataFrame({s*pbar[USE_GOOD]:np.log(nutrient_adequacy_ratio(xref/
↪4,my_prices(pbar[USE_GOOD]*s,j=USE_GOOD),dbar))[UseNutrients] for s in␣
↪scale}).T

fig,ax = plt.subplots()
ax.plot(ndf['phos'],ndf.index)
ax.axhline(pbar[USE_GOOD])
ax.axvline(0)
```

```
ax.set_ylabel('Price')
ax.set_xlabel('log nutrient adequacy ratio')
ax.set_title("Nutrient Adequacy Ratio by Price of %s" % USE_GOOD)
```

<IPython.core.display.Javascript object>

<IPython.core.display.HTML object>

[64]: Text(0.5, 1.0, 'Nutrient Adequacy Ratio by Price of Fresh fish')

### 1.0.5 Determining which food items should be subsidized in our economic policy alleviating inadequacies in fat consumption

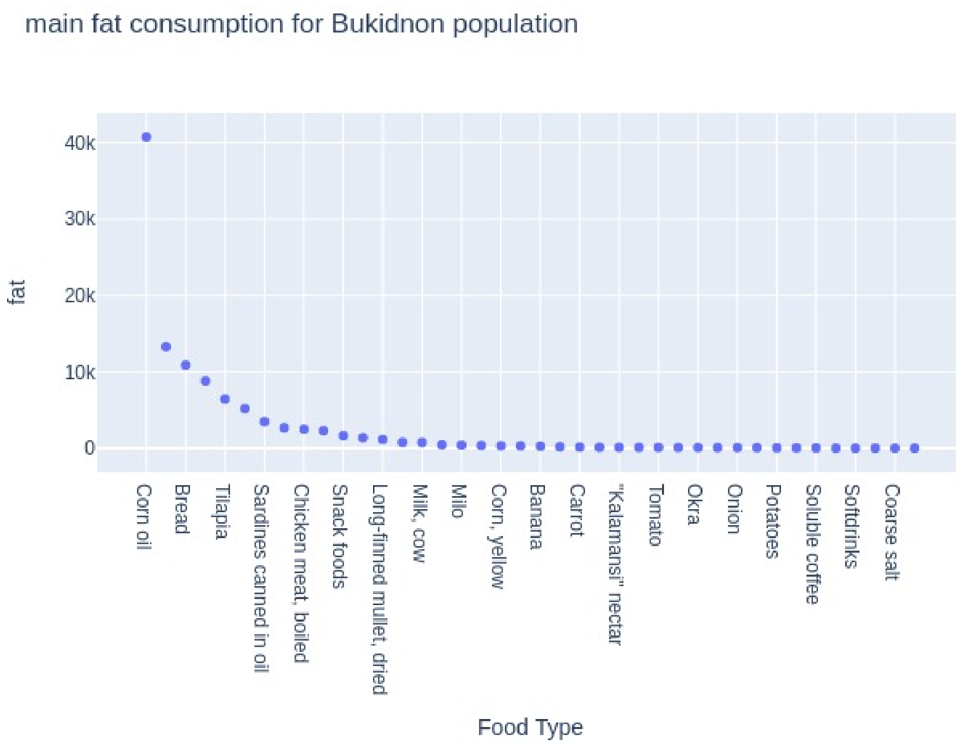
[68]:
```
#consumption function for plotting nutrient consumption based on food types
def consumption (nutrient):
    consumption = qhat_fct[use]
    for col in consumption.columns:
        consumption[col] = consumption[col] * fct[nutrient].loc[col]
    nutrient_df = pd.DataFrame({nutrient: consumption.mean()}).
 ↪sort_values(by=nutrient, ascending=False)
    fig_nutrient = px.scatter(nutrient_df, x=list(nutrient_df.index),␣
 ↪y=nutrient_df[nutrient], title='main ' + nutrient + ' consumption for␣
 ↪Bukidnon population')
    fig_nutrient.update_xaxes(title_text='Food Type')
    return fig_nutrient
```

[69]:
```
#high content functino for plotting foods with high nutrients.
def high_content (nutrient):
    high = fct[nutrient]
    high = pd.DataFrame({nutrient: high}).sort_values(by = nutrient,␣
 ↪ascending=False)
    fig = px.scatter(high, x=list(high.index), y=high[nutrient], title='high '␣
 ↪+ nutrient + ' foods based on FCT')
    fig.update_xaxes(title_text='Food Type')
    return fig
```

[67]:
```
# calculate the fat consumption per household by type of food consumed
fat_consump = consumption('fat')
fat_consump.show('jpg')
```

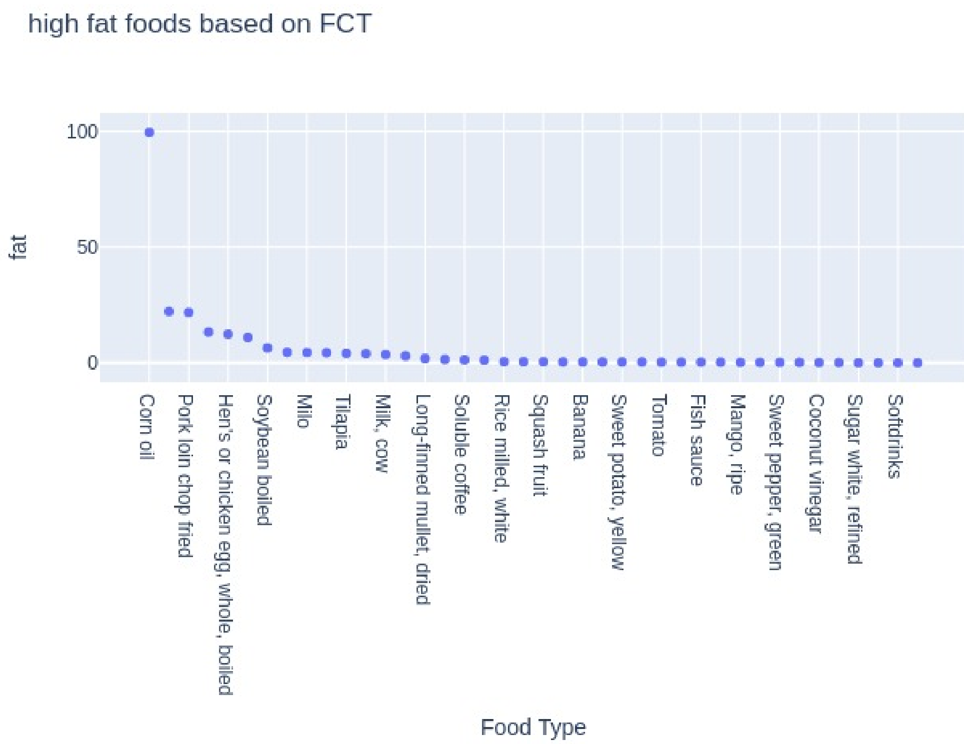
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.




[45]:
```
high_fat = high_content('fat')
high_fat.show('jpg')
```

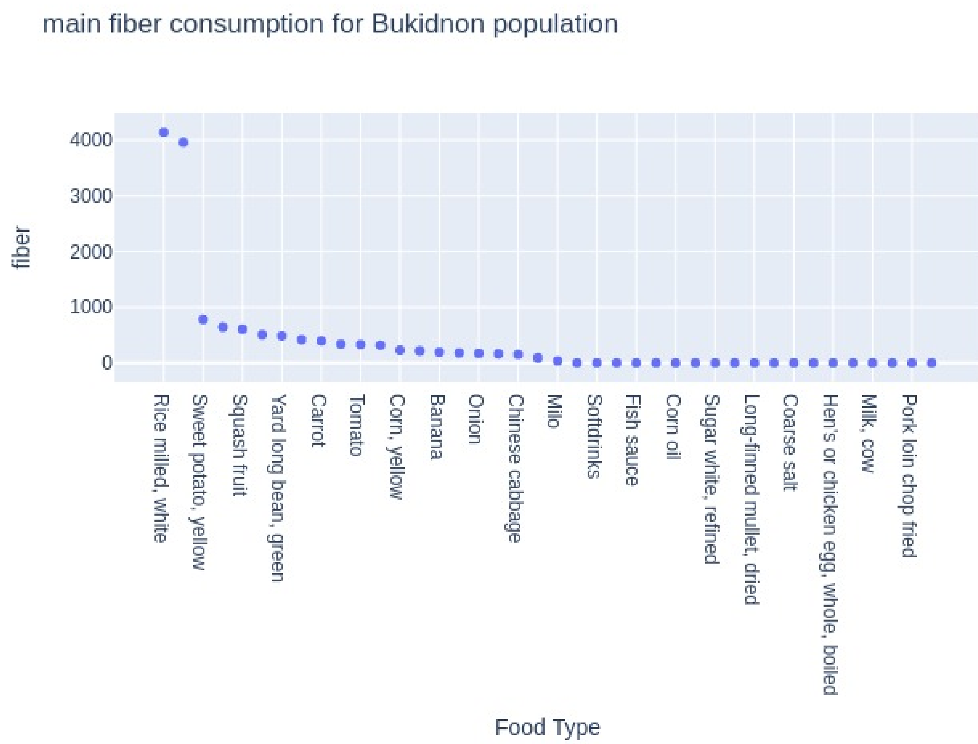
```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```




### 1.0.6 alleviating inadequacies in fiber consumption

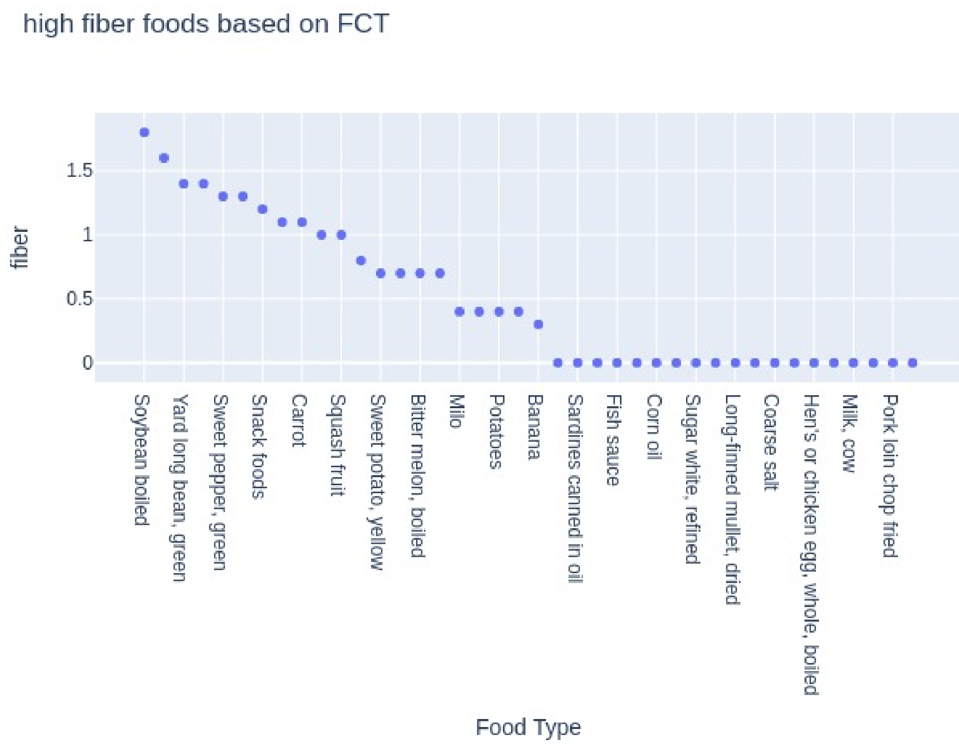
[46]:
```python
# calculate the fiberconsumption per household by type of food consumed
fiber_consump = consumption('fiber')
fiber_consump.show('jpg')
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```




[47]:
```
high_fiber = high_content('fiber')
high_fiber.show('jpg')
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```

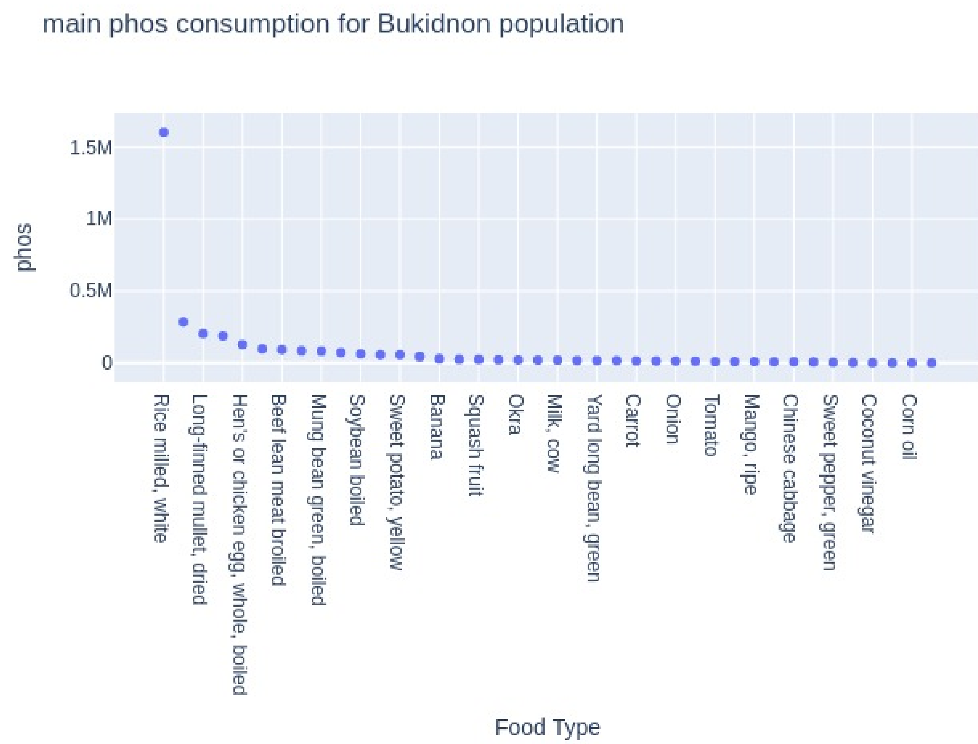



## 1.1 other consumption rates

### 1.1.1 phosphorous

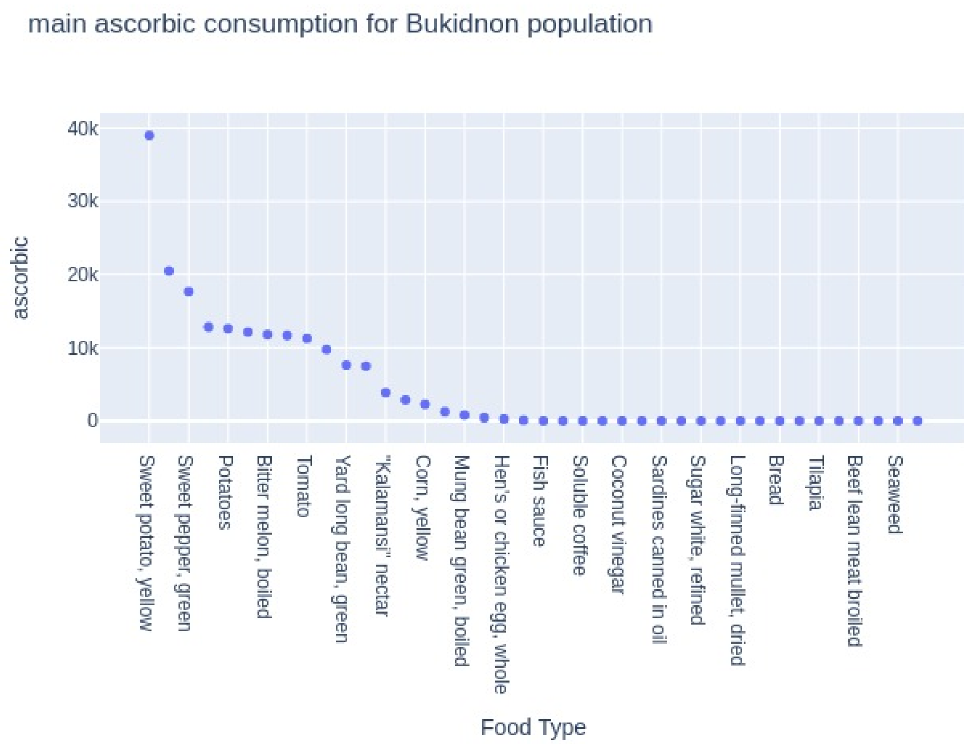
[48]:
```
# phosphorous consumption
import plotly.express as px
phosphorous_consump = consumption('phos')
phosphorous_consump.show('jpg')
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```



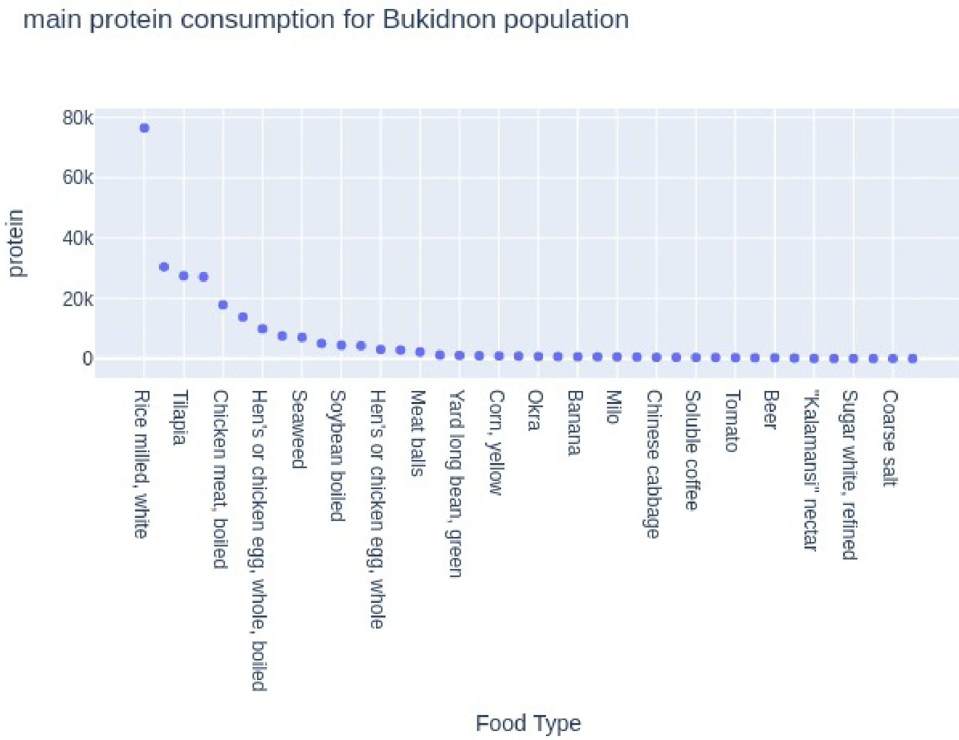

[49]:
```
# niacin consumption
import plotly.express as px
ascorbic_consump = consumption('ascorbic')
ascorbic_consump.show('jpg')
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```




[50]:
```python
# protein consumption
import plotly.express as px
protein_consump = consumption('protein')
protein_consump.show('jpg')
```

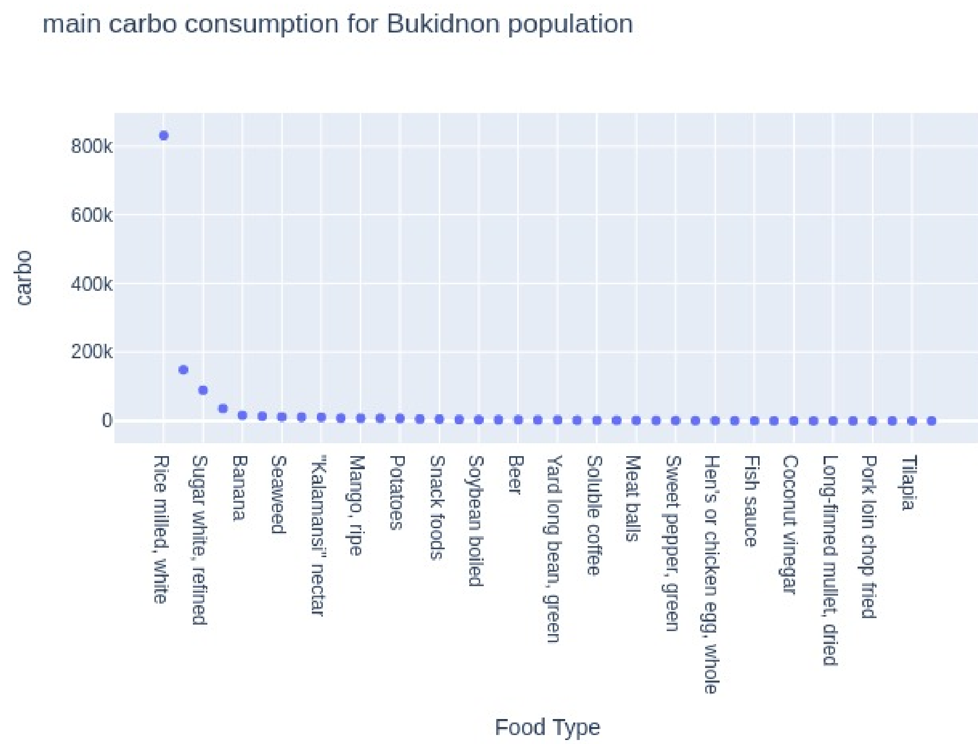
```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```




[51]:

```
# carbohydrate consumption
import plotly.express as px
carbo_consump = consumption('carbo')
carbo_consump.show('jpg')
```

```
/opt/conda/lib/python3.9/site-packages/plotly/io/_renderers.py:396:
DeprecationWarning:

distutils Version classes are deprecated. Use packaging.version instead.
```

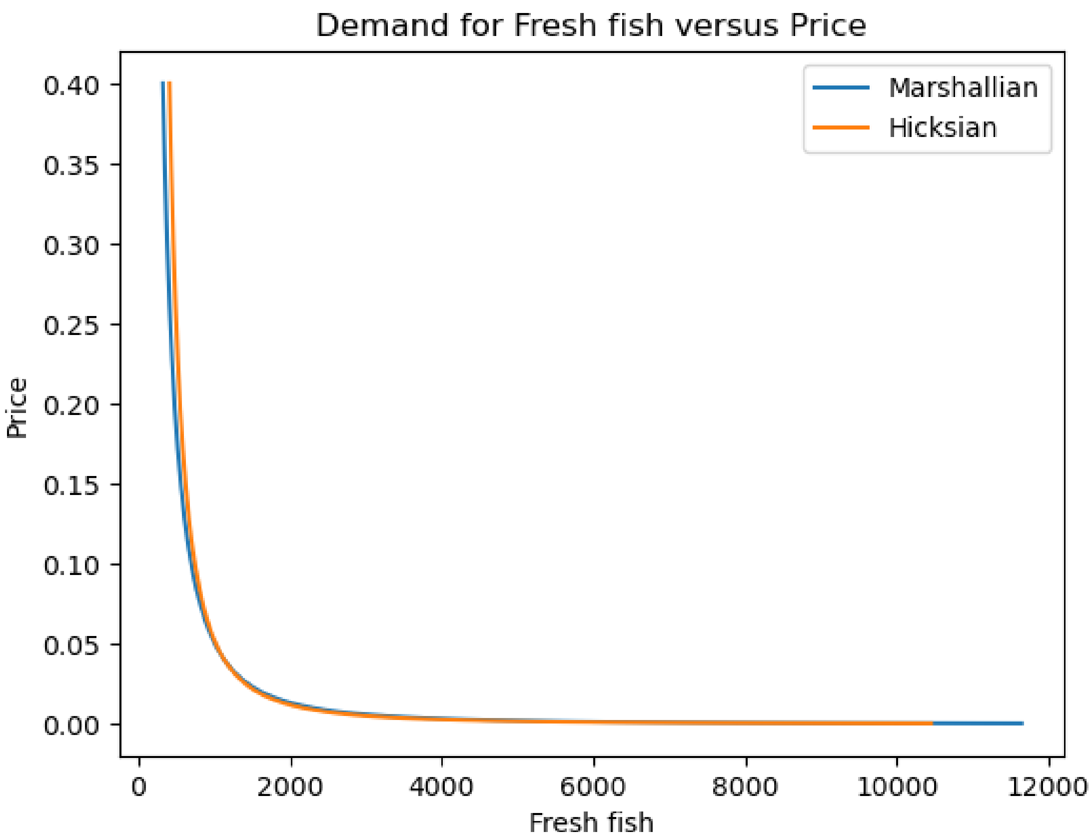



#### 1.1.2 Policy Costs

#### 1.1.3 Marshallian vs. Hicksian Demand Curves

[79]:
```
import matplotlib.pyplot as plt
%matplotlib inline

my_j = 'Fresh fish'

P = np.geomspace(.01,10,50)*pbar[my_j]

# Utility of median household, given prices
U0 = result.indirect_utility(xref,pbar)

plt.plot([result.demands(xref,my_prices(p0,j=my_j))[my_j] for p0 in P],P)
plt.plot([result.demands(U0,my_prices(p0,j=my_j),type="Hicksian")[my_j] for p0␣
 ↪in P],P)
plt.ylabel('Price')
plt.xlabel(my_j)
plt.legend(("Marshallian","Hicksian"))
plt.title("Demand for %s versus Price" % my_j)
```

[79]: Text(0.5, 1.0, 'Demand for Fresh fish versus Price')




[71]:
```
def compensating_variation(U0,p0,p1):
    x0 = result.expenditure(U0,p0)
    x1 = result.expenditure(U0,p1)

    return x1-x0

def revenue(U0,p0,p1,type='Marshallian'):
    """(Un)Compensated revenue from taxes changing vector of prices from p0 to␣
↪p1.

    Note that this is only for *demand* side (i.e., if supply perfectly␣
↪elastic).
    """

    dp = p1 - p0 # Change in prices

    c = result.demands(U0,p1,type=type)
```

```python
    dp,c = dp.align(c,join='inner')

    return dp.T@c


def deadweight_loss(U0,p0,p1):
    """
    Deadweight loss of tax/subsidy scheme creating wedge in prices from p0 to␣
 ↪p1.

    Note that this is only for *demand* side (i.e., if supply perfectly␣
 ↪elastic).
    """
    cv = compensating_variation(U0,p0,p1)

    return cv - revenue(U0,p0,p1,type='Hicksian')
```

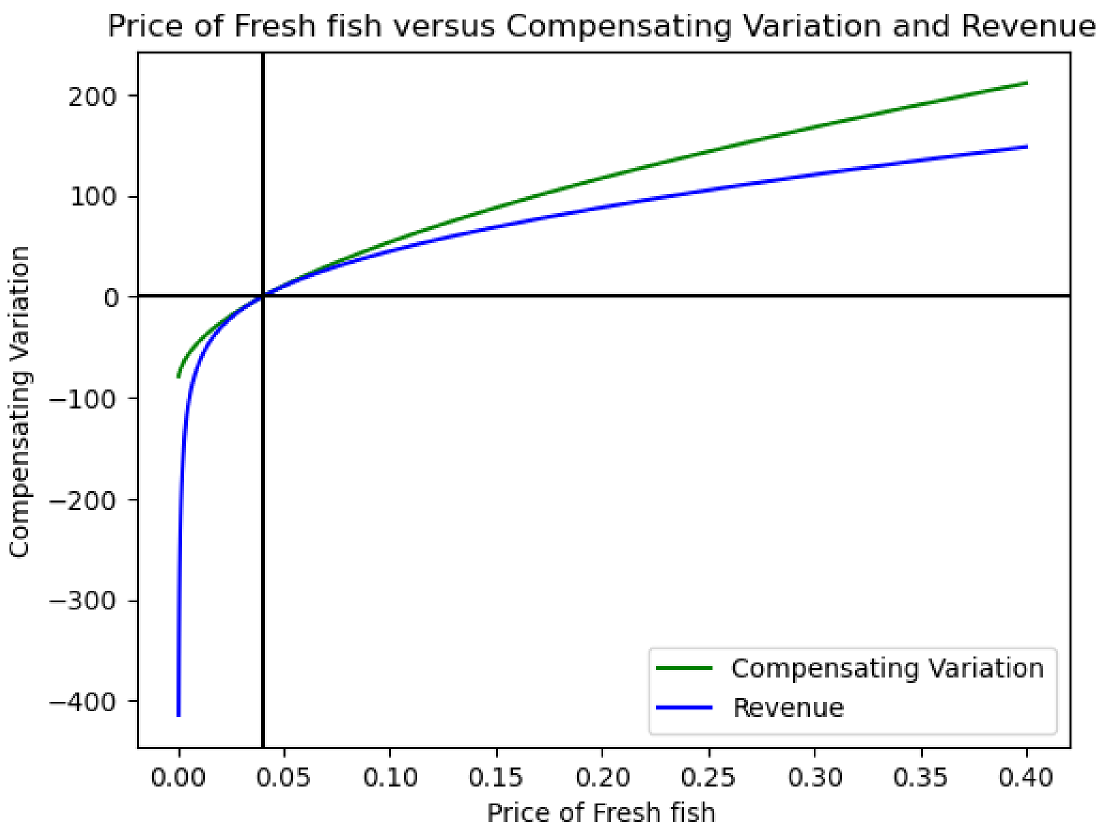
### 1.1.4 Price Changes, Revenue, and Compensating Variation

Examine effects of price changes on revenue (if price change due to a tax or subsidy) and compensating variation.

[76]:
```python
my_j = 'Fresh fish'

fig, ax1 = plt.subplots()

ax1.plot(P,[compensating_variation(U0,pbar,my_prices(p0,j=my_j)) for p0 in P],␣
 ↪color = 'green')
ax1.set_xlabel(f"Price of {my_j}")
ax1.set_ylabel("Compensating Variation")

ax1.plot(P,[revenue(U0,pbar,my_prices(p0,j=my_j),type='Hicksian') for p0 in␣
 ↪P],'k', color = 'blue')
ax1.legend(('Compensating Variation','Revenue'))
ax1.axhline(0, color = 'black')
ax1.axvline(pbar.loc[my_j], color = 'black')
ax1.set_title(f'Price of {my_j} versus Compensating Variation and Revenue')
```

```
/tmp/ipykernel_29/167596395.py:9: UserWarning:

color is redundantly defined by the 'color' keyword argument and the fmt string
"k" (-> color=(0.0, 0.0, 0.0, 1)). The keyword argument will take precedence.
```

[76]:
```
Text(0.5, 1.0, 'Price of Fresh fish versus Compensating Variation and Revenue')
```



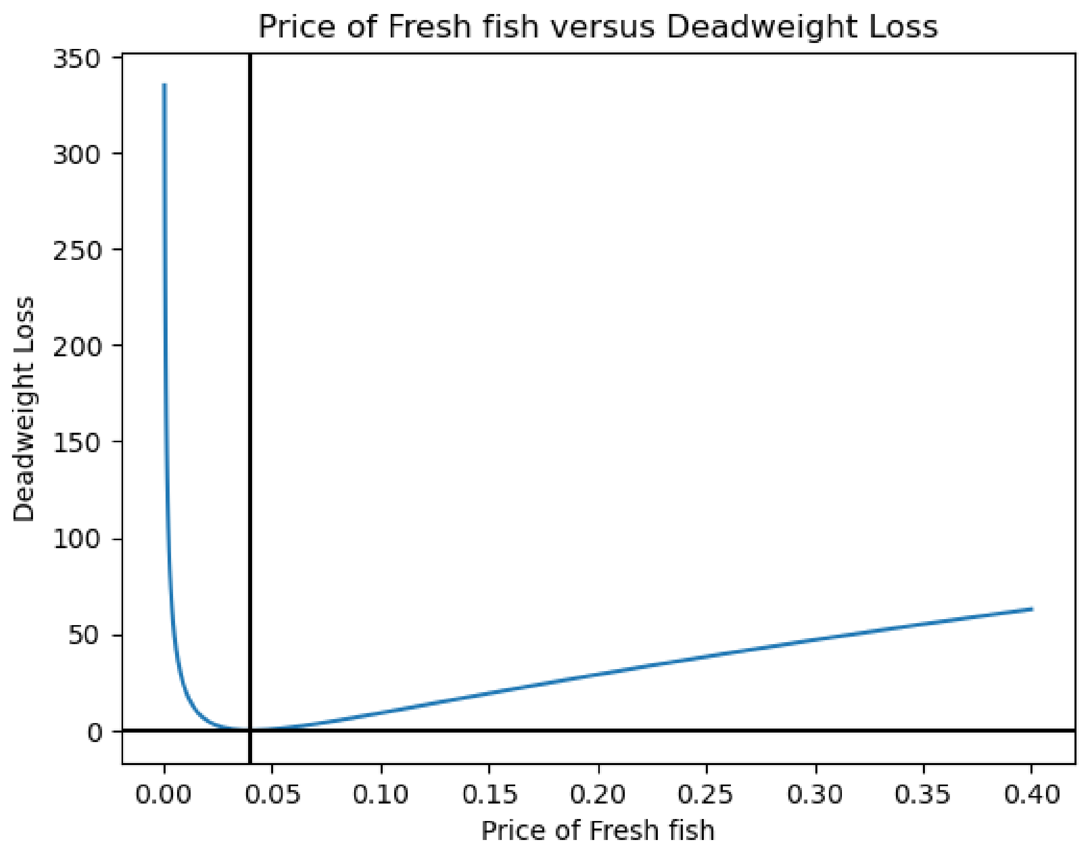

changing the price of "good". verticle blue = price of 'good' , compensating variation = 'no loss at all'. As we increase the price of 'good', there is an increase in loss of consumer surplus. Black line = revenue, the revenue line increases at a decreasing rate as we increase the price of the 'good', as people replace the 'good' with some other food surplus.

### 1.1.5 Deadweight Loss

Differences between revenue and compensating variation is deadweight-loss:

[74]:
```
fig, ax1 = plt.subplots()

ax1.plot(P,[deadweight_loss(U0,pbar,my_prices(p0,j=my_j)) for p0 in P])
ax1.set_xlabel("Price of %s" % my_j)
ax1.set_ylabel("Deadweight Loss")
ax1.set_title("Price of %s versus Deadweight Loss" % my_j)
ax1.axhline(0, color = 'black')
ax1.axvline(pbar.loc[my_j], color = 'black')
```

[74]:
```
<matplotlib.lines.Line2D at 0x7f23044fe430>
```




[80]:
```
def nar_price_by_good (good):
    scale = np.geomspace(.01,2,50)

    USE_GOOD = good

    ndf = pd.DataFrame({s*pbar[USE_GOOD]:np.log(nutrient_adequacy_ratio(xref/
 ↪4,my_prices(pbar[USE_GOOD]*s,j=USE_GOOD),dbar))[UseNutrients] for s in␣
 ↪scale}).T
    fig,ax = plt.subplots()
    ax.plot(ndf.index,ndf['phos'],label = 'phosphorous')
    ax.plot(ndf.index,ndf['carbo'], label = 'carbs')
    ax.plot(ndf.index,ndf['protein'], label = 'protein')
    ax.plot(ndf.index,ndf['ascorbic'], label = 'ascorbic acid')
    ax.axhline(0, color = 'black')
    ax.axvline(pbar[USE_GOOD],color = 'black')
    ax.legend(loc = 'best')
    ax.set_ylabel('log nutrient adequacy ratio')
    ax.set_xlabel('Price')
    ax.set_title("Log Nutrient Adequacy Ratio by Price of %s" % USE_GOOD)
    return fig.show()
```

[81]:

```
nar_price_by_good('Fresh fish')
```