Import Data Libraries

In [2]:
```
import pandas as pd
!pip install pyarrow

import ipywidgets
from ipywidgets import interactive, fixed, interact, Dropdown
```

```
Collecting pyarrow
  Using cached pyarrow-7.0.0-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (2
6.7 MB)
Requirement already satisfied: numpy>=1.16.6 in /opt/conda/lib/python3.9/site-packages
(from pyarrow) (1.21.5)
Installing collected packages: pyarrow
Successfully installed pyarrow-7.0.0
```

In [3]:
```
!pip install -r requirements.txt
import numpy as np
import sys
!pip install eep153-tools
!pip install gspread-pandas

from eep153_tools.sheets import read_sheets
import cfe
```

```
Collecting CFEDemands>=0.4.1
  Using cached CFEDemands-0.4.1-py2.py3-none-any.whl (39 kB)
Collecting ConsumerDemands
  Using cached ConsumerDemands-0.3.dev0-py2.py3-none-any.whl (12 kB)
Requirement already satisfied: gspread>=4.0.1 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 10)) (4.0.1)
Requirement already satisfied: matplotlib>=3.3.4 in /opt/conda/lib/python3.9/site-packag
es (from -r requirements.txt (line 13)) (3.4.3)
Requirement already satisfied: numpy>=1.21.5 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 17)) (1.21.5)
Collecting oauth2client>=4.1.3
  Using cached oauth2client-4.1.3-py2.py3-none-any.whl (98 kB)
Requirement already satisfied: pandas>=1.3.5 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 25)) (1.3.5)
Requirement already satisfied: plotly>=5.1.0 in /opt/conda/lib/python3.9/site-packages
(from -r requirements.txt (line 28)) (5.2.1)
Collecting eep153_tools>=0.11
  Using cached eep153_tools-0.11-py2.py3-none-any.whl (4.4 kB)
Processing /home/jovyan/.cache/pip/wheels/20/7e/30/7d702acd6a1e89911301cd9dbf9cb9870ca80
c0e64bc2cde23/gnupg-2.3.1-py3-none-any.whl
Requirement already satisfied: google-auth-oauthlib>=0.4.1 in /opt/conda/lib/python3.9/s
ite-packages (from gspread>=4.0.1->-r requirements.txt (line 10)) (0.4.5)
Requirement already satisfied: google-auth>=1.12.0 in /opt/conda/lib/python3.9/site-pack
ages (from gspread>=4.0.1->-r requirements.txt (line 10)) (2.6.2)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.9/site-packages (f
rom matplotlib>=3.3.4->-r requirements.txt (line 13)) (0.11.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /opt/conda/lib/python3.9/site-packag
es (from matplotlib>=3.3.4->-r requirements.txt (line 13)) (1.4.2)
Requirement already satisfied: pyparsing>=2.2.1 in /opt/conda/lib/python3.9/site-package
s (from matplotlib>=3.3.4->-r requirements.txt (line 13)) (3.0.7)
Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/python3.9/site-packages
(from matplotlib>=3.3.4->-r requirements.txt (line 13)) (8.3.2)
Requirement already satisfied: python-dateutil>=2.7 in /opt/conda/lib/python3.9/site-pac
kages (from matplotlib>=3.3.4->-r requirements.txt (line 13)) (2.8.0)
Requirement already satisfied: httplib2>=0.9.1 in /opt/conda/lib/python3.9/site-packages
(from oauth2client>=4.1.3->-r requirements.txt (line 20)) (0.20.4)
Requirement already satisfied: pyasn1-modules>=0.0.5 in /opt/conda/lib/python3.9/site-pa
```

```
ckages (from oauth2client>=4.1.3->-r requirements.txt (line 20)) (0.2.8)
Requirement already satisfied: six>=1.6.1 in /opt/conda/lib/python3.9/site-packages (fro
m oauth2client>=4.1.3->-r requirements.txt (line 20)) (1.16.0)
Requirement already satisfied: pyasn1>=0.1.7 in /opt/conda/lib/python3.9/site-packages
(from oauth2client>=4.1.3->-r requirements.txt (line 20)) (0.4.8)
Requirement already satisfied: rsa>=3.1.4 in /opt/conda/lib/python3.9/site-packages (fro
m oauth2client>=4.1.3->-r requirements.txt (line 20)) (4.8)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.9/site-packages (f
rom pandas>=1.3.5->-r requirements.txt (line 25)) (2021.1)
Requirement already satisfied: tenacity>=6.2.0 in /opt/conda/lib/python3.9/site-packages
(from plotly>=5.1.0->-r requirements.txt (line 28)) (8.0.1)
Requirement already satisfied: psutil>=1.2.1 in /opt/conda/lib/python3.9/site-packages
(from gnupg->-r requirements.txt (line 31)) (5.9.0)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /opt/conda/lib/python3.9/site
-packages (from google-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirements.txt (line 1
0)) (1.3.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /opt/conda/lib/python3.9/site-p
ackages (from google-auth>=1.12.0->gspread>=4.0.1->-r requirements.txt (line 10)) (5.0.
0)
Requirement already satisfied: oauthlib>=3.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirem
ents.txt (line 10)) (3.2.0)
Requirement already satisfied: requests>=2.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirem
ents.txt (line 10)) (2.26.0)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.9/site-packa
ges (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gsprea
d>=4.0.1->-r requirements.txt (line 10)) (2019.11.28)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /opt/conda/lib/python3.9/site-pa
ckages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib>=0.4.1->gsp
read>=4.0.1->-r requirements.txt (line 10)) (1.25.7)
Requirement already satisfied: charset-normalizer~=2.0.0; python_version >= "3" in /opt/
conda/lib/python3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->googl
e-auth-oauthlib>=0.4.1->gspread>=4.0.1->-r requirements.txt (line 10)) (2.0.0)
Requirement already satisfied: idna<4,>=2.5; python_version >= "3" in /opt/conda/lib/pyt
hon3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthl
ib>=0.4.1->gspread>=4.0.1->-r requirements.txt (line 10)) (2.8)
Installing collected packages: CFEDemands, ConsumerDemands, oauth2client, eep153-tools,
gnupg
Successfully installed CFEDemands-0.4.1 ConsumerDemands-0.3.dev0 eep153-tools-0.11 gnupg
-2.3.1 oauth2client-4.1.3
Requirement already satisfied: eep153-tools in /opt/conda/lib/python3.9/site-packages
(0.11)
Requirement already satisfied: gspread-pandas in /opt/conda/lib/python3.9/site-packages
(2.3.0)
Requirement already satisfied: six in /opt/conda/lib/python3.9/site-packages (from gspre
ad-pandas) (1.16.0)
Requirement already satisfied: google-auth-oauthlib in /opt/conda/lib/python3.9/site-pac
kages (from gspread-pandas) (0.4.5)
Requirement already satisfied: decorator in /opt/conda/lib/python3.9/site-packages (from
gspread-pandas) (5.0.9)
Requirement already satisfied: gspread>=3.0.0 in /opt/conda/lib/python3.9/site-packages
(from gspread-pandas) (4.0.1)
Requirement already satisfied: pandas>=0.20.0 in /opt/conda/lib/python3.9/site-packages
(from gspread-pandas) (1.3.5)
Requirement already satisfied: google-auth in /opt/conda/lib/python3.9/site-packages (fr
om gspread-pandas) (2.6.2)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /opt/conda/lib/python3.9/site
-packages (from google-auth-oauthlib->gspread-pandas) (1.3.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/conda/lib/python3.9/site-p
ackages (from pandas>=0.20.0->gspread-pandas) (2.8.0)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.9/site-packages (f
rom pandas>=0.20.0->gspread-pandas) (2021.1)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.9/site-packages
(from pandas>=0.20.0->gspread-pandas) (1.21.5)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /opt/conda/lib/python3.9/site-p
```

```
ackages (from google-auth->gspread-pandas) (5.0.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /opt/conda/lib/python3.9/site-pa
ckages (from google-auth->gspread-pandas) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3.6" in /opt/conda/lib/
python3.9/site-packages (from google-auth->gspread-pandas) (4.8)
Requirement already satisfied: requests>=2.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-pandas) (2.26.0)
Requirement already satisfied: oauthlib>=3.0.0 in /opt/conda/lib/python3.9/site-packages
(from requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-pandas) (3.2.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /opt/conda/lib/python3.9/site-pac
kages (from pyasn1-modules>=0.2.1->google-auth->gspread-pandas) (0.4.8)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /opt/conda/lib/python3.9/site-pa
ckages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-pa
ndas) (1.25.7)
Requirement already satisfied: certifi>=2017.4.17 in /opt/conda/lib/python3.9/site-packa
ges (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthlib->gspread-panda
s) (2019.11.28)
Requirement already satisfied: charset-normalizer~=2.0.0; python_version >= "3" in /opt/
conda/lib/python3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->googl
e-auth-oauthlib->gspread-pandas) (2.0.0)
Requirement already satisfied: idna<4,>=2.5; python_version >= "3" in /opt/conda/lib/pyt
hon3.9/site-packages (from requests>=2.0.0->requests-oauthlib>=0.7.0->google-auth-oauthl
ib->gspread-pandas) (2.8)
Missing dependencies for OracleDemands.
```

[A] Population, and Supporting Expenditure Data

Parquet Files Cleaning & DataFrame Establishment

We acquired our data from the Indian National Sample Survey (NSS). These original parque files contain data from a very large pool of households from 35 states; the following parts establish dataframes for our choosen Maharashtra population.

In [4]:
```
#food expenditure in Rupee
food_price = pd.read_parquet('x.parquet', engine = 'pyarrow').unstack('i')
food_price
```

Out[4]:

	i	apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...	toddy
j	**Frequency**												
410001101	**Monthly**	20.0	121.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	120.0	...	NaN
410001102	**Monthly**	160.0	60.0	NaN	40.0	60.0	NaN	NaN	NaN	NaN	15.0	...	NaN
410001103	**Monthly**	40.0	195.0	NaN	NaN	50.0	NaN	NaN	NaN	NaN	60.0	...	NaN
410001201	**Monthly**	40.0	130.0	NaN	NaN	20.0	NaN	NaN	NaN	NaN	90.0	...	NaN
410001202	**Monthly**	NaN	65.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	60.0	...	NaN
...	**...**	...	...	...	...	...	...	...	...	...	...	...	...
799981301	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982101	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982201	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982202	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN
799982301	**Monthly**	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN

101660 rows × 164 columns

In [5]:
```python
#food quantity
food_quant = pd.read_parquet('q.parquet', engine = 'pyarrow').reset_index()
food_quant
```

Out[5]:

	j	i	unit	Frequency	total_quantity
0	410001101	apple	kg	Monthly	250.0
1	410001101	arhar (tur)	kg	Monthly	2000.0
2	410001101	besan	kg	Monthly	2000.0
3	410001101	black pepper	gm	Monthly	20.0
4	410001101	brinjal	kg	Monthly	5000.0
...	...	...	...	...	...
4423639	799982301	tomato	kg	Monthly	3000.0
4423640	799982301	turmeric	gm	Monthly	300.0
4423641	799982301	urd	kg	Monthly	1000.0
4423642	799982301	wheat/atta - P.D.S.	kg	Monthly	10000.0
4423643	799982301	wheat/atta - other sources	kg	Monthly	20000.0

4423644 rows × 5 columns

In [6]:
```python
#nutritional content
nutritient = pd.read_parquet('n.parquet', engine = 'pyarrow')
nutritient
```

Out[6]:

	calories per unit(kcal)	fat per unit(gm)	i	protein per unit(gm)	rural	t	unit
1	3280.000000	13.00	ragi	73.00	NaN	50	kg
4	1100.000000	2.00	other cereal subs.	16.00	NaN	50	kg
5	3420.000000	36.00	maize-other sources	111.00	NaN	50	kg
7	3420.000000	36.00	maize - pds	111.00	NaN	50	kg
8	3360.000000	13.00	barley	115.00	NaN	50	kg
...	...	...	...	...	...	...	...
145	24.700001	0.95	other served processed food	0.70	0.0	68	Re
146	21.100000	0.85	cake, pastry, prepared sweets	0.20	0.0	68	Re
147	28.500000	0.17	biscuits, chocolates	0.35	0.0	68	Re
148	24.700001	0.95	papad, bhujia, namkeen, mixture, chanachur	0.70	0.0	68	Re
149	24.700001	0.95	other packaged processed food	0.70	0.0	68	Re

277 rows × 7 columns

In [7]:
```python
# age-sex composition
pop = pd.read_parquet('z.parquet', engine = 'pyarrow')
pop
```

Out[7]:

	k	rural	m	religion	social group	Males 0-1	Males 1-5	Males 5-10	Males 10-15	Males 15-20	Males 20-30	...	Males 60-	Fema

												100
j												
410001101	Urban	Gujarat	Hinduism	Other backward class	0	0	0	0	0	2	...	0
410001102	Urban	Gujarat	Christianity	Others	0	0	0	1	0	0	...	0
410001103	Urban	Gujarat	Hinduism	Others	0	0	0	0	0	3	...	0
410001201	Urban	Gujarat	Christianity	Others	0	0	0	0	0	1	...	1
410001202	Urban	Gujarat	Hinduism	Others	0	0	0	0	0	0	...	0
...	...	...	...	...	...	...	...	...	...	...	...	...
799981301	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	1	1	0	...	0
799982101	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	1	1	0	...	0
799982201	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	1	2	0	...	0
799982202	Rural	Jammu & Kashmir	Hinduism	Others	0	0	2	1	0	0	...	0
799982301	Rural	Jammu & Kashmir	Hinduism	Others	0	0	0	0	0	0	...	1

101662 rows × 22 columns

In [8]:
```
#total household expenditure in Rupee
expenditure = pd.read_parquet('total_expenditures.parquet', engine = 'pyarrow')
expenditure
```

Out[8]:

	total_value
j	
410001101	7813
410001102	3573
410001103	9359
410001201	5671
410001202	6169
...	...
799981301	3842
799982101	2736
799982201	3378
799982202	3221
799982301	3777

101660 rows × 1 columns

In [42]:
```
pop.info()
pop.religion.value_counts()
#from the output, we can see that Maharashtra has the second most data points (8043 hous
#so, this would further insure the validity of our following estimation
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 101662 entries, 410001101 to 799982301
Data columns (total 22 columns):
 #   Column          Non-Null Count   Dtype 
---  ------          --------------   ----- 
 0   rural           101662 non-null  object
 1   m               101662 non-null  object
 2   religion        101659 non-null  object
 3   social group    101648 non-null  object
 4   Males 0-1       101662 non-null  int64 
 5   Males 1-5       101662 non-null  int64 
 6   Males 5-10      101662 non-null  int64 
 7   Males 10-15     101662 non-null  int64 
 8   Males 15-20     101662 non-null  int64 
 9   Males 20-30     101662 non-null  int64 
 10  Males 30-50     101662 non-null  int64 
 11  Males 50-60     101662 non-null  int64 
 12  Males 60-100    101662 non-null  int64 
 13  Females 0-1     101662 non-null  int64 
 14  Females 1-5     101662 non-null  int64 
 15  Females 5-10    101662 non-null  int64 
 16  Females 10-15   101662 non-null  int64 
 17  Females 15-20   101662 non-null  int64 
 18  Females 20-30   101662 non-null  int64 
 19  Females 30-50   101662 non-null  int64 
 20  Females 50-60   101662 non-null  int64 
 21  Females 60-100  101662 non-null  int64 
dtypes: int64(18), object(4)
memory usage: 17.8+ MB
```

Out[42]:
```
Hinduism          77062
Islam             13136
Christianity       7070
Sikhism            2016
Buddhism           1094
Others              956
Jainism             322
Zoroastrianism        3
Name: religion, dtype: int64
```

Here are some helper functions to extrapolate data for the chosen population from the larger raw dataframe

The `filter_pop` function takes a raw dataframe and households characteristics as arguments and returns a `DataFrame` for the choosen population segement. The optional arguemnts help if you want to target specific demographic groups in the choosen state

Input Parameters:

- **df**: the name of the raw population df you want to extrapolate from
- **state**: an str (any state name from the 35 states)
- **rural**: optional; an str ('Rural' or 'Urban')
- **religion**: optional; an str ('Hinduism', 'Islam', 'Christianity', 'Sikhism', 'Buddhism', 'Others', 'Jainism', or 'Zoroastrianism')

In [11]:
```
def filter_pop(df, state, rural = None, religion = None):
    new = df.loc[df['m'] == state]
    if rural != None:
        new = new.loc[new['rural'] == rural]
    if religion != None:
        new= new.loc[new['religion'] == religion]
    return new
```

The `get_id` function takes a raw dataframe and households characteristics as arguments, uses the `filter_pop` function, and returns a list of household IDs for the chosen population

Input Parameters:

- **df**: the raw df you want to extrapolate from
- **state**: an str (any state name from the 35 states)
- **rural**: optional; an str ('Rural' or 'Urban')
- **religion**: optional; an str ('Hinduism', 'Islam', 'Christianity', 'Sikhism', 'Buddhism', 'Others', 'Jainism', or 'Zoroastrianism')

In [12]:
```
def get_id(df, state, rural = None, religion = None):
    ids = filter_pop(df = pop, state = state, rural = rural, religion = religion).index
    return ids
```

The `match_info` function takes a raw dataframe and household_ids and returns a sliced df for the particular selected households

Input Parameters:

- **ids**: list of column ids
- **df**: the raw df you want to extrapolate from

In [13]:
```
def match_info(ids, df):
    n = df.reset_index()
    new = n[n['j'].isin(ids)]
    return new
```

[A] Estimate Demand System

Establish and format DataFrames for the chosen population: Surveyed Households from the state of Maharashtra, India

In [14]:
```
maharashtra_id =get_id(df = pop, state = 'Maharashtra')
maharashtra_id
```

Out[14]:
```
Index(['421001201', '421001202', '421001203', '421001204', '421002201',
       '421002202', '421002203', '421002204', '421011101', '421011102',
       ...
       '756982202', '756982301', '756991101', '756991102', '756991201',
       '756991202', '756991203', '756991204', '756991301', '756991302'],
      dtype='object', name='j', length=8043)
```

In [15]:
```
maha_food_quant = match_info(maharashtra_id, food_quant)
maha_food_quant
```

Out[15]:

	index	j	i	unit	Frequency	total_quantity
332920	332920	421001201	arhar (tur)	kg	Monthly	1000.0
332921	332921	421001201	besan	kg	Monthly	500.0

332922	332922	421001201	biscuits, chocolates	Re	Monthly	0.0
332923	332923	421001201	bread (bakery)	kg	Monthly	1000.0
332924	332924	421001201	brinjal	kg	Monthly	1000.0
...	...	...	...	...	...	...
3494160	3494160	756991302	suji, rawa	kg	Monthly	1000.0
3494161	3494161	756991302	tea : cups	no.	Monthly	20.0
3494162	3494162	756991302	tea : leaf	gm	Monthly	350.0
3494163	3494163	756991302	tomato	kg	Monthly	3500.0
3494164	3494164	756991302	turmeric	gm	Monthly	150.0

387953 rows × 6 columns

In [16]:
```
maha_tol_exp = match_info(maharashtra_id, expenditure)
maha_tol_exp
```

Out[16]:

	j	total_value
7577	421001201	4857
7578	421001202	5246
7579	421001203	2725
7580	421001204	4750
7581	421002201	5207
...	...	...
78734	756991202	2497
78735	756991203	2028
78736	756991204	2833
78737	756991301	3706
78738	756991302	4566

8043 rows × 2 columns

In [17]:
```
maha_food_exp = match_info(maharashtra_id, food_price)

maha_food_exp.drop('Frequency', inplace=True, axis=1) #drop unecessary columns
maha_food_exp.columns.name = 'i'
maha_food_exp.set_index('j')
maha_food_exp = maha_food_exp.groupby('i',axis=1).sum()
maha_food_exp = maha_food_exp.replace(0,np.nan) # Replace zeros with NaN
maha_food_exp.rename(columns={maha_food_exp.columns[-1] :'j'}, inplace=True)

# add the time 't' and market 'm' column
#since the data is from one year (2016) and one market (maharashtra), equate all to 1
maha_food_exp.insert(loc=165, column='t', value=1)
maha_food_exp.insert(loc=166, column='m', value=1)

# Take logs of expenditures and name the new df 'y'
y = np.log(maha_food_exp.set_index(['j','t','m']))
y
```

```
/opt/conda/lib/python3.9/site-packages/pandas/core/generic.py:4150: PerformanceWarning:
dropping on a non-lexsorted multi-index without a level parameter may impact performanc
```

```
e.
  obj = obj._drop_axis(labels, axis, level=level, errors=errors)
```

Out[17]:

		i	apple	arhar (tur)	baby food	bajra & products	banana	barley & products	beef	beer	berries	besan	...	t
j	**t**	**m**												
421001201	**1**	**1**	NaN	4.317488	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.401197	...	
421001202	**1**	**1**	NaN	4.382027	NaN	NaN	4.248495	NaN	NaN	NaN	NaN	3.401197	...	
421001203	**1**	**1**	NaN	NaN	NaN	NaN	2.890372	NaN	NaN	NaN	NaN	NaN	...	
421001204	**1**	**1**	NaN	NaN	NaN	NaN	3.555348	NaN	NaN	NaN	NaN	3.401197	...	
421002201	**1**	**1**	NaN	4.317488	NaN	NaN	3.555348	NaN	NaN	NaN	NaN	3.401197	...	
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...	
756991202	**1**	**1**	NaN	3.401197	NaN	NaN	3.688879	NaN	NaN	NaN	2.484907	NaN	...	
756991203	**1**	**1**	NaN	4.700480	NaN	NaN	NaN	NaN	NaN	NaN	2.564949	NaN	...	
756991204	**1**	**1**	NaN	4.828314	NaN	NaN	NaN	NaN	NaN	NaN	2.708050	NaN	...	
756991301	**1**	**1**	NaN	4.867534	NaN	NaN	3.091042	NaN	NaN	NaN	2.484907	NaN	...	
756991302	**1**	**1**	NaN	4.574711	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	

8043 rows × 164 columns

In [18]:

```python
maha_pop = match_info(maharashtra_id, pop)
maha_pop

# add the time 't' and market 'm' column
#since the data is from one year (2016) and one market (maharashtra), equate all to 1
maha_pop['m'] = 1
maha_pop['t'] = 1
maha_pop.columns.name = 'k'
maha_pop.set_index(['j','t','m'],inplace=True)
maha_pop.drop(maha_pop.columns[0:3], inplace=True, axis=1) #drop unecessary columns

# calculate and add new column 'log Hsize'
maha_pop['log Hsize'] = np.log(maha_pop.sum(axis=1).values)
maha_pop
```

Out[18]:

		k	Males 0-1	Males 1-5	Males 5-10	Males 10-15	Males 15-20	Males 20-30	Males 30-50	Males 50-60	Males 60-100	Females 0-1	Females 1-5	Fema 5
j	**t**	**m**												
421001201	**1**	**1**	0	1	1	0	0	0	1	0	0	0	0	
421001202	**1**	**1**	0	0	0	0	0	0	1	0	0	0	1	
421001203	**1**	**1**	0	0	0	0	0	1	0	0	0	0	0	
421001204	**1**	**1**	0	0	0	0	0	0	1	0	0	0	0	
421002201	**1**	**1**	0	1	0	0	0	0	1	0	0	0	0	
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...	
756991202	**1**	**1**	0	0	0	0	0	0	1	0	0	0	0	
756991203	**1**	**1**	0	0	0	0	0	0	0	0	1	0	0	
756991204	**1**	**1**	0	0	0	0	0	0	1	0	0	1	1	
756991301	**1**	**1**	0	0	0	0	0	1	0	1	0	0	0	

756991302	**1**	**1**	0	0	0	0	1	0	1	0	0	0	0

8043 rows × 19 columns

Estimation

1.First step:

Recall that there are two steps to estimation; the first step involves estimating the “reduced form” linear regression

$$y_{it}^j = a_{it} + \delta_i' z_t^j + \epsilon_{it}^j.$$

In [19]:
```
result = cfe.Result(y=y,z=maha_pop)
```

This creates a complicated “Result” object, with lots of different attributes. Note from below that attributes y and z are now defined.

In [20]:
```
result
```

Out[20]:

xarray.Result

▸ Dimensions: (**k**: 19, **j**: 8043, **t**: 1, **m**: 1, **i**: 103)

▾ Coordinates:

j	(j)	object	'421001201' ... '756991302'
t	(t)	int64	1
m	(m)	int64	1
i	(i)	<U50	'apple' ... 'wheat/atta - other ...
k	(k)	<U14	'Males 0-1' ... 'log Hsize'

▸ Data variables: (20)

▸ Attributes: (10)

In [44]:
```
#the Result class has code to estimate the "reduced form" in one line:
result.get_reduced_form()
```

```
/opt/conda/lib/python3.9/site-packages/cfe/estimation.py:425: UserWarning: No variation
in: (1, 1)
  warnings.warn("No variation in: %s" % str(constant))
```

After running this we can examine the estimated coefficients δ:

In [22]:
```
result.delta.to_dataframe().unstack('k')
```

Out[22]:

k	Males 0-1	Males 1-5	Males 5-10	Males 10-15	Males 15-20	Males 20-30	Males 30-50	Males 50-60	Males 60-100
i									
apple	0.116241	-0.010087	-0.016225	0.042034	0.025789	0.072390	0.185028	0.152401	0.118404
arhar (tur)	-0.023166	-0.038610	-0.012056	0.004052	0.023918	0.061794	0.095395	0.091041	0.096935

bajra & products	0.252834	-0.010578	0.042047	0.071540	0.075980	0.164270	0.045495	0.089150	0.175357
banana	-0.025035	-0.032487	-0.016979	0.010445	0.022264	0.067411	0.131955	0.091155	0.082210
besan	-0.073333	-0.018965	0.036798	0.001278	0.024174	0.085924	0.085044	0.100227	0.111893
...	...	...	...	...	...	...	...	...	...
urd	0.093142	0.039835	0.003065	0.024844	0.053146	0.083538	0.066379	0.026303	0.099115
vanaspati, margarine	0.166406	0.025756	0.048454	0.023660	-0.034821	0.101674	0.074322	0.152296	0.219197
watermelon	0.109513	0.093756	0.096730	0.033754	0.091002	0.080101	0.006049	0.032390	0.097625
wheat/atta - P.D.S.	-0.053065	-0.129640	-0.060660	-0.009596	0.041966	-0.045329	-0.067712	-0.085848	-0.069854
wheat/atta - other sources	-0.091201	-0.073899	-0.066786	0.006375	-0.028890	0.013290	0.096776	0.101193	0.056519

103 rows × 19 columns

Also the good-time constants a_{it} (this captures the effects of prices):

However, in our data, we only have data from 1 year, so the time factor is mostly irrelevant; this won't create a problem in our estimation because although we only have 1 year, the data is from a large pool of households (8043 j values)

In [23]:
```
result.a.to_dataframe().unstack('i')
```

Out[23]:

	i	**apple**	**arhar (tur)**	**bajra & products**	**banana**	**besan**	**biscuits, chocolates**	**black pepper**	**bread (bakery)**	**brinjal**	**cabbage**	**...**
t	**m**											
1	**1**	4.337676	3.689784	3.436197	3.184263	2.69299	3.432596	1.979749	3.462497	2.353381	2.359734	...

1 rows × 103 columns

2.Second step:

The second step involves using Singular Value Decomposition to find the rank one matrix that best approximates the residuals e_{it}^{j}. This can be interpreted as

$$-\beta_i \log \lambda_t^j,$$

where the $\log \lambda_t^j$ is the log of the marginal utility of expenditures (MUE) for household j at time t, and where β_i are the corresponding “Frisch elasticities” that tell us how much demand changes as the MUE falls.

Estimates can also be computed as a one-liner:

In [24]:
```
result.get_beta(as_df=True)
```

Out[24]:
```
i
apple                             0.451570
arhar (tur)                       0.177062
```

```
bajra & products            -0.085787
banana                       0.329504
besan                        0.171622
                               ...
urd                          0.155062
vanaspati, margarine         0.243740
watermelon                   0.256393
wheat/atta - P.D.S.          0.057134
wheat/atta - other sources   0.116349
Name: beta, Length: 103, dtype: float64
```

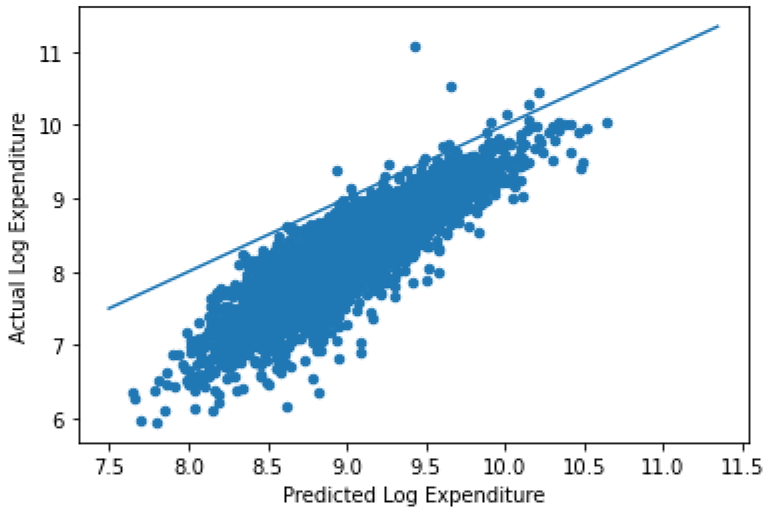
3. Assessment of Fit

In [35]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.cm as cm

xbar = np.exp(result.y).sum(['m','i']).to_dataframe('xbar').replace(0,np.nan).squeeze()
xhat = result.get_predicted_expenditures().sum(['m','i']).to_dataframe('xhat').replace(0

# Make dataframe of actual & predicted
df = pd.DataFrame({'Actual Log Expenditure':np.log(xbar),'Predicted Log Expenditure':np.

df.plot.scatter(x='Predicted Log Expenditure',y='Actual Log Expenditure')

# Add 45 degree line
v = plt.axis()
vmin = np.max([v[0],v[2]])
vmax = np.max([v[1],v[3]])
plt.plot([vmin,vmax],[vmin,vmax])
```

Out[35]:

```
[<matplotlib.lines.Line2D at 0x7fe1ee521a90>]
```



In [47]:

```
#save estimate result in datahub
result.to_dataset('maharashtra.ds')
```

Out[47]:

xarray.Dataset

▸ Dimensions: (**j**: 8043, **i**: 103, **k**: 19, **t**: 1, **m**: 1, **kp**: 19)

▾ Coordinates:

j	(j)	object	'421001201' ... '756991302'
t	(t)	int64	1
m	(m)	int64	1

```
i      (i)    <U50 'apple' ... 'wheat/atta - other ...
k      (k)    <U14 'Males 0-1' ... 'log Hsize'
kp     (kp)   <U14 'Males 0-1' ... 'log Hsize'
```

▸ Data variables: (20)

▸ Attributes: (0)

4. Infer Prices

In [48]:
```
# Estimates most things (not counting std errors for betas).
xhat = result.get_predicted_expenditures(as_df = True)
result.get_beta(as_df=True).sort_values(ascending=False).tail(30) # Check sanity...
```

Out[48]:
```
i
groundnut                                              0.138778
chillis (green)                                        0.135773
chira                                                  0.129129
refined oil [sunflower, soyabean, saffola, etc.]       0.123606
ingredients for pan                                    0.121903
oilseeds                                               0.121774
turmeric                                               0.116570
wheat/atta - other sources                             0.116349
suji, rawa                                             0.113621
jeera                                                  0.112667
other pulses                                           0.109483
garlic                                                 0.108950
cereal substitutes  (tapioca, jackfruit seed etc.)     0.106252
lpg                                                    0.103953
kerosene-pds                                           0.092297
jowar & products                                       0.089634
groundnut oil                                          0.087579
candle                                                 0.080314
salt                                                   0.066118
wheat/atta - P.D.S.                                    0.057134
sugar - other sources                                  0.053577
gram (split)                                           0.030520
peas-pulses                                            0.023732
gram (whole)                                           0.020225
other tobacco products                                 0.018432
other pulse products                                   0.009157
firewood & chips                                      -0.037526
bajra & products                                      -0.085787
dry chillies                                          -0.088085
matches                                               -0.160492
Name: beta, dtype: float64
```

In [33]:
```
xhat
```

Out[33]:

		i	apple	arhar (tur)	bajra & products	banana	besan	biscuits, chocolates	black pepper	bread (bakery)
j	**t**	**m**								
421001201	**1**	**1**	155.764284	136.298187	79.535101	60.900000	39.677284	133.857843	18.543350	69.585119
421001202	**1**	**1**	161.288050	116.774955	73.359981	60.288393	36.532337	112.739126	17.467538	59.847131
421001204	**1**	**1**	150.780726	132.287215	84.336430	61.225979	40.647621	101.944674	16.652758	63.723065
421002201	**1**	**1**	154.981870	130.251596	82.364117	60.336993	39.478636	110.866183	16.897120	65.505165
421002202	**1**	**1**	131.668819	133.504481	89.331760	57.264063	37.238290	117.003045	18.598272	61.101826
...	**...**	**...**	...	...	...	...	...	...	...	...

756991202	**1**	**1**	58.779462	64.247291	61.870750	26.620794	21.066255	29.174252	8.253264	30.887101
756991203	**1**	**1**	45.399259	56.314497	82.701845	21.184194	20.042832	21.155324	7.115237	27.142407
756991204	**1**	**1**	29.924709	74.171263	108.505533	18.431859	21.400973	19.424488	5.934119	25.510268
756991301	**1**	**1**	72.576328	113.662452	142.056537	36.048330	36.173957	36.916379	10.001800	41.103161
756991302	**1**	**1**	95.180292	130.856510	107.777791	46.766355	37.734430	57.181961	13.291108	48.406165

7787 rows × 103 columns

```
In [ ]:
```