Project_4_Code

April 30, 2023

[1]:
```
!pip install -r requirements.txt
```

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Requirement already satisfied: CFEDemands>=0.4.1 in
/opt/conda/lib/python3.9/site-packages (from -r requirements.txt (line 5))
(0.5.4)
Requirement already satisfied: gspread>=5.0.1 in /opt/conda/lib/python3.9/site-
packages (from -r requirements.txt (line 7)) (5.8.0)
Requirement already satisfied: gspread_pandas>=3.2.0 in
/opt/conda/lib/python3.9/site-packages (from -r requirements.txt (line 8))
(3.2.2)
Requirement already satisfied: oauth2client>=4.1.3 in
/opt/conda/lib/python3.9/site-packages (from -r requirements.txt (line 11))
(4.1.3)
Requirement already satisfied: eep153_tools>=0.11 in
/opt/conda/lib/python3.9/site-packages (from -r requirements.txt (line 21))
(0.11)
Requirement already satisfied: python-gnupg in /opt/conda/lib/python3.9/site-
packages (from -r requirements.txt (line 22)) (0.5.0)
Requirement already satisfied: ConsumerDemands in /opt/conda/lib/python3.9/site-
packages (from -r requirements.txt (line 24)) (0.4.1.dev0)
Requirement already satisfied: pytest>=7.1.1 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (7.2.2)
Requirement already satisfied: scipy>=1.7.3 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (1.10.1)
Requirement already satisfied: dvc>=2.18.1 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.55.0)
Requirement already satisfied: xarray>=0.20.1 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2023.4.2)
Requirement already satisfied: statsmodels>=0.13.2 in
/opt/conda/lib/python3.9/site-packages (from CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.13.5)
Requirement already satisfied: matplotlib>=3.5.1 in
/opt/conda/lib/python3.9/site-packages (from CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.5.3)
Requirement already satisfied: numpy>=1.21.5 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (1.21.6)
Requirement already satisfied: joblib>=1.1.0 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (1.2.0)
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Requirement already satisfied: ray>=2.0.0 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.4.0)
Requirement already satisfied: pandas>=1.4.2 in /opt/conda/lib/python3.9/site-
packages (from CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.0.1)
Requirement already satisfied: google-auth-oauthlib>=0.4.1 in
/opt/conda/lib/python3.9/site-packages (from gspread>=5.0.1->-r requirements.txt
(line 7)) (0.4.5)
Requirement already satisfied: google-auth>=1.12.0 in
/opt/conda/lib/python3.9/site-packages (from gspread>=5.0.1->-r requirements.txt
(line 7)) (2.17.1)
Requirement already satisfied: decorator in /opt/conda/lib/python3.9/site-
packages (from gspread_pandas>=3.2.0->-r requirements.txt (line 8)) (5.0.9)
Requirement already satisfied: rsa>=3.1.4 in /opt/conda/lib/python3.9/site-
packages (from oauth2client>=4.1.3->-r requirements.txt (line 11)) (4.9)
Requirement already satisfied: httplib2>=0.9.1 in /opt/conda/lib/python3.9/site-
packages (from oauth2client>=4.1.3->-r requirements.txt (line 11)) (0.22.0)
Requirement already satisfied: pyasn1>=0.1.7 in /opt/conda/lib/python3.9/site-
packages (from oauth2client>=4.1.3->-r requirements.txt (line 11)) (0.4.8)
Requirement already satisfied: six>=1.6.1 in /opt/conda/lib/python3.9/site-
packages (from oauth2client>=4.1.3->-r requirements.txt (line 11)) (1.16.0)
Requirement already satisfied: pyasn1-modules>=0.0.5 in
/opt/conda/lib/python3.9/site-packages (from oauth2client>=4.1.3->-r
requirements.txt (line 11)) (0.2.7)
Requirement already satisfied: platformdirs<4,>=3.1.1 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.2.0)
Requirement already satisfied: pyparsing>=2.4.7 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.0.9)
Requirement already satisfied: funcy>=1.14 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.0)
Requirement already satisfied: voluptuous>=0.11.7 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.13.1)
Requirement already satisfied: shtab<2,>=1.3.4 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.6.1)
Requirement already satisfied: iterative-telemetry>=0.0.7 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.0.8)
Requirement already satisfied: colorama>=0.3.9 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.4.4)
Requirement already satisfied: ruamel.yaml>=0.17.11 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.17.21)
Requirement already satisfied: psutil>=5.8 in /opt/conda/lib/python3.9/site-
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packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(5.9.4)
Requirement already satisfied: pydot>=1.2.4 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.4.2)
Requirement already satisfied: tomlkit>=0.11.1 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.11.8)
Requirement already satisfied: configobj>=5.0.6 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (5.0.8)
Requirement already satisfied: dvc-http>=2.29.0 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (2.30.2)
Requirement already satisfied: pygtrie>=2.3.2 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.5.0)
Requirement already satisfied: pathspec>=0.10.3 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.11.1)
Requirement already satisfied: grandalf<1,>=0.7 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.8)
Requirement already satisfied: dvc-studio-client<1,>=0.6.1 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.8.0)
Requirement already satisfied: tabulate>=0.8.7 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.9.0)
Requirement already satisfied: scmrepo<2,>=1.0.0 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (1.0.2)
Requirement already satisfied: rich>=12 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(13.3.5)
Requirement already satisfied: dpath<3,>=2.1.0 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.1.5)
Requirement already satisfied: networkx>=2.5 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.6.3)
Requirement already satisfied: packaging>=19 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(21.3)
Requirement already satisfied: flatten-dict<1,>=0.4.1 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.4.2)
Requirement already satisfied: requests>=2.22 in /opt/conda/lib/python3.9/site-
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packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.26.0)
Requirement already satisfied: dvc-render<0.4.0,>=0.3.1 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.3.1)
Requirement already satisfied: flufl.lock>=5 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(7.1.1)
Requirement already satisfied: tqdm<5,>=4.63.1 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(4.65.0)
Requirement already satisfied: distro>=1.3 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.8.0)
Requirement already satisfied: shortuuid>=0.5 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.0.11)
Requirement already satisfied: zc.lockfile>=1.2.1 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.0.post1)
Requirement already satisfied: dvc-data<0.48,>=0.47.1 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.47.2)
Requirement already satisfied: dvc-task<1,>=0.2.0 in
/opt/conda/lib/python3.9/site-packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.2.1)
Requirement already satisfied: hydra-core>=1.1 in /opt/conda/lib/python3.9/site-
packages (from dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.3.2)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in
/opt/conda/lib/python3.9/site-packages (from google-
auth>=1.12.0->gspread>=5.0.1->-r requirements.txt (line 7)) (5.3.0)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/opt/conda/lib/python3.9/site-packages (from google-auth-
oauthlib>=0.4.1->gspread>=5.0.1->-r requirements.txt (line 7)) (1.3.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/conda/lib/python3.9/site-packages (from
matplotlib>=3.5.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (1.4.4)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/conda/lib/python3.9/site-packages (from
matplotlib>=3.5.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (4.39.3)
Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/python3.9/site-
packages (from matplotlib>=3.5.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (9.4.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.9/site-
packages (from matplotlib>=3.5.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (0.11.0)
Requirement already satisfied: python-dateutil>=2.7 in
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/opt/conda/lib/python3.9/site-packages (from
matplotlib>=3.5.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.8.2)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.9/site-
packages (from pandas>=1.4.2->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2023.3)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.9/site-
packages (from pandas>=1.4.2->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2023.3)
Requirement already satisfied: tomli>=1.0.0 in /opt/conda/lib/python3.9/site-
packages (from pytest>=7.1.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.0.1)
Requirement already satisfied: pluggy<2.0,>=0.12 in
/opt/conda/lib/python3.9/site-packages (from
pytest>=7.1.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (1.0.0)
Requirement already satisfied: exceptiongroup>=1.0.0rc8 in
/opt/conda/lib/python3.9/site-packages (from
pytest>=7.1.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (1.1.1)
Requirement already satisfied: attrs>=19.2.0 in /opt/conda/lib/python3.9/site-
packages (from pytest>=7.1.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(23.1.0)
Requirement already satisfied: iniconfig in /opt/conda/lib/python3.9/site-
packages (from pytest>=7.1.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.0.0)
Requirement already satisfied: jsonschema in /opt/conda/lib/python3.9/site-
packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(4.17.3)
Requirement already satisfied: grpcio<=1.51.3,>=1.32.0 in
/opt/conda/lib/python3.9/site-packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (1.43.0)
Requirement already satisfied: protobuf!=3.19.5,>=3.15.3 in
/opt/conda/lib/python3.9/site-packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.19.6)
Requirement already satisfied: aiosignal in /opt/conda/lib/python3.9/site-
packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.3.1)
Requirement already satisfied: virtualenv<20.21.1,>=20.0.24 in
/opt/conda/lib/python3.9/site-packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (20.21.0)
Requirement already satisfied: click>=7.0 in /opt/conda/lib/python3.9/site-
packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(8.0.4)
Requirement already satisfied: filelock in /opt/conda/lib/python3.9/site-
packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(3.10.7)
Requirement already satisfied: pyyaml in /opt/conda/lib/python3.9/site-packages
(from ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (6.0)
Requirement already satisfied: msgpack<2.0.0,>=1.0.0 in
/opt/conda/lib/python3.9/site-packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r
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requirements.txt (line 5)) (1.0.5)
Requirement already satisfied: frozenlist in /opt/conda/lib/python3.9/site-
packages (from ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.3.3)
Requirement already satisfied: patsy>=0.5.2 in /opt/conda/lib/python3.9/site-
packages (from statsmodels>=0.13.2->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (0.5.3)
Requirement already satisfied: dvc-objects<1,>=0.21.1 in
/opt/conda/lib/python3.9/site-packages (from dvc-
data<0.48,>=0.47.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (0.21.2)
Requirement already satisfied: dictdiffer>=0.8.1 in
/opt/conda/lib/python3.9/site-packages (from dvc-
data<0.48,>=0.47.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (0.9.0)
Requirement already satisfied: nanotime>=0.5.2 in /opt/conda/lib/python3.9/site-
packages (from dvc-data<0.48,>=0.47.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.5.2)
Requirement already satisfied: sqltrie<1,>=0.3.1 in
/opt/conda/lib/python3.9/site-packages (from dvc-
data<0.48,>=0.47.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (0.3.1)
Requirement already satisfied: diskcache>=5.2.1 in
/opt/conda/lib/python3.9/site-packages (from dvc-
data<0.48,>=0.47.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (5.6.1)
Requirement already satisfied: aiohttp-retry>=2.5.0 in
/opt/conda/lib/python3.9/site-packages (from dvc-
http>=2.29.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.8.3)
Requirement already satisfied: fsspec[http] in /opt/conda/lib/python3.9/site-
packages (from dvc-http>=2.29.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (2023.3.0)
Requirement already satisfied: dulwich in /opt/conda/lib/python3.9/site-packages
(from dvc-studio-client<1,>=0.6.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (0.21.3)
Requirement already satisfied: celery<6,>=5.2.0 in
/opt/conda/lib/python3.9/site-packages (from dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(5.2.7)
Requirement already satisfied: kombu<6,>=5.2.0 in /opt/conda/lib/python3.9/site-
packages (from dvc-task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (5.2.4)
Requirement already satisfied: atpublic>=2.3 in /opt/conda/lib/python3.9/site-
packages (from flufl.lock>=5->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.1.1)
Requirement already satisfied: antlr4-python3-runtime==4.9.* in
/opt/conda/lib/python3.9/site-packages (from hydra-
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core>=1.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (4.9.3)
Requirement already satisfied: omegaconf<2.4,>=2.2 in
/opt/conda/lib/python3.9/site-packages (from hydra-
core>=1.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.3.0)
Requirement already satisfied: appdirs in /opt/conda/lib/python3.9/site-packages
(from iterative-telemetry>=0.0.7->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (1.4.4)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.9/site-packages (from
requests>=2.22->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2021.10.8)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.9/site-
packages (from requests>=2.22->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.1)
Requirement already satisfied: charset-normalizer~=2.0.0 in
/opt/conda/lib/python3.9/site-packages (from
requests>=2.22->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.0.0)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/opt/conda/lib/python3.9/site-packages (from
requests>=2.22->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.26.7)
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>=5.0.1->-r requirements.txt (line 7)) (3.2.2)
Requirement already satisfied: markdown-it-py<3.0.0,>=2.2.0 in
/opt/conda/lib/python3.9/site-packages (from
rich>=12->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.2.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/opt/conda/lib/python3.9/site-packages (from
rich>=12->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5)) (2.14.0)
Requirement already satisfied: ruamel.yaml.clib>=0.2.6 in
/opt/conda/lib/python3.9/site-packages (from
ruamel.yaml>=0.17.11->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (0.2.7)
Requirement already satisfied: pygit2>=1.10.0 in /opt/conda/lib/python3.9/site-
packages (from scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (1.12.0)
Requirement already satisfied: asyncssh<3,>=2.13.1 in
/opt/conda/lib/python3.9/site-packages (from
scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(2.13.1)
Requirement already satisfied: gitpython>3 in /opt/conda/lib/python3.9/site-
packages (from scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.1.31)
Requirement already satisfied: distlib<1,>=0.3.6 in
/opt/conda/lib/python3.9/site-packages (from
virtualenv<20.21.1,>=20.0.24->ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt
```

```
(line 5)) (0.3.6)
Requirement already satisfied: setuptools in /opt/conda/lib/python3.9/site-
packages (from zc.lockfile>=1.2.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (67.6.1)
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in
/opt/conda/lib/python3.9/site-packages (from
jsonschema->ray>=2.0.0->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.19.3)
Requirement already satisfied: aiohttp in /opt/conda/lib/python3.9/site-packages
(from aiohttp-retry>=2.5.0->dvc-http>=2.29.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.8.4)
Requirement already satisfied: cryptography>=3.1 in
/opt/conda/lib/python3.9/site-packages (from
asyncssh<3,>=2.13.1->scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (3.4.8)
Requirement already satisfied: typing-extensions>=3.6 in
/opt/conda/lib/python3.9/site-packages (from
asyncssh<3,>=2.13.1->scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (4.5.0)
Requirement already satisfied: vine<6.0,>=5.0.0 in
/opt/conda/lib/python3.9/site-packages (from celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(5.0.0)
Requirement already satisfied: click-didyoumean>=0.0.3 in
/opt/conda/lib/python3.9/site-packages (from celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.3.0)
Requirement already satisfied: click-plugins>=1.1.1 in
/opt/conda/lib/python3.9/site-packages (from celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.1.1)
Requirement already satisfied: billiard<4.0,>=3.6.4.0 in
/opt/conda/lib/python3.9/site-packages (from celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(3.6.4.0)
Requirement already satisfied: click-repl>=0.2.0 in
/opt/conda/lib/python3.9/site-packages (from celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.2.0)
Requirement already satisfied: gitdb<5,>=4.0.1 in /opt/conda/lib/python3.9/site-
packages (from
gitpython>3->scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (4.0.10)
Requirement already satisfied: amqp<6.0.0,>=5.0.9 in
/opt/conda/lib/python3.9/site-packages (from kombu<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(5.1.1)
Requirement already satisfied: mdurl~=0.1 in /opt/conda/lib/python3.9/site-
```

```
packages (from markdown-it-
py<3.0.0,>=2.2.0->rich>=12->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt
(line 5)) (0.1.2)
Requirement already satisfied: cffi>=1.9.1 in /opt/conda/lib/python3.9/site-
packages (from
pygit2>=1.10.0->scmrepo<2,>=1.0.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r
requirements.txt (line 5)) (1.14.6)
Requirement already satisfied: orjson in /opt/conda/lib/python3.9/site-packages
(from sqltrie<1,>=0.3.1->dvc-
data<0.48,>=0.47.1->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line
5)) (3.8.11)
Requirement already satisfied: async-timeout<5.0,>=4.0.0a3 in
/opt/conda/lib/python3.9/site-packages (from aiohttp->aiohttp-retry>=2.5.0->dvc-
http>=2.29.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(4.0.2)
Requirement already satisfied: multidict<7.0,>=4.5 in
/opt/conda/lib/python3.9/site-packages (from aiohttp->aiohttp-retry>=2.5.0->dvc-
http>=2.29.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(6.0.4)
Requirement already satisfied: yarl<2.0,>=1.0 in /opt/conda/lib/python3.9/site-
packages (from aiohttp->aiohttp-retry>=2.5.0->dvc-
http>=2.29.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(1.8.2)
Requirement already satisfied: pycparser in /opt/conda/lib/python3.9/site-
packages (from cffi>=1.9.1->pygit2>=1.10.0->scmrepo<2,>=1.0.0->dvc>=2.18.1->CFED
emands>=0.4.1->-r requirements.txt (line 5)) (2.20)
Requirement already satisfied: prompt-toolkit in /opt/conda/lib/python3.9/site-
packages (from click-repl>=0.2.0->celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(3.0.38)
Requirement already satisfied: smmap<6,>=3.0.1 in /opt/conda/lib/python3.9/site-
packages (from gitdb<5,>=4.0.1->gitpython>3->scmrepo<2,>=1.0.0->dvc>=2.18.1->CFE
Demands>=0.4.1->-r requirements.txt (line 5)) (5.0.0)
Requirement already satisfied: wcwidth in /opt/conda/lib/python3.9/site-packages
(from prompt-toolkit->click-repl>=0.2.0->celery<6,>=5.2.0->dvc-
task<1,>=0.2.0->dvc>=2.18.1->CFEDemands>=0.4.1->-r requirements.txt (line 5))
(0.2.6)
```

[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]:
```python
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')}
```

[78]:
```python
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.
Key available for students@eep153.iam.gserviceaccount.com.
```

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

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)
```

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[10]:
```
# 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]:
```
#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)
px.bar(top5_calorie, x=list(top5_calorie.index), y=top5_calorie['calories'],␣
 ↪title='Top 5 Calorie Contributors')
```

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'})
```

[19]:

```
# 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 0x7f8aea9f7df0>
```

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

[20]:
```
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 0x7f8aea934910>
```

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]: 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 = 'Pork'

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 Pork')
```

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

[26]:
```
rdi = get_clean_sheet(Phillippines_Data,
                    sheet='RDI')
```

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

[27]:
```
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

[33]:
```
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.

[34]:
```
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>
```

[34]: 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.

[35]:
```
scale = np.geomspace(.01,2,50)

USE_GOOD = 'Beef'

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>

[35]: Text(0.5, 1.0, 'Nutrient Adequacy Ratio by Price of Beef')

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

[52]:
```
#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
```

[77]:
```
#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
```

[64]:
```
# calculate the fat consumption per household by type of food consumed
fat_consump = consumption('fat')
fat_consump.show()
```

[65]:
```
high_fat = high_content('fat')
high_fat.show()
```

1.0.6 alleviating inadequacies in fiber consumption

[66]:
```
# calculate the fiberconsumption per household by type of food consumed
fiber_consump = consumption('fiber')
fiber_consump.show()
```

[67]:
```
high_fiber = high_content('fiber')
high_fiber.show()
```

1.1 other consumption rates

1.1.1 phosphorous

[73]:
```
# phosphorous consumption
import plotly.express as px
phosphorous_consump = consumption('phos')
phosphorous_consump.show()
```

[72]:
```
# niacin consumption
import plotly.express as px
niacin_consump = consumption('niacin')
niacin_consump.show()
```

[75]:
```
# protein consumption
import plotly.express as px
protein_consump = consumption('protein')
protein_consump.show()
```

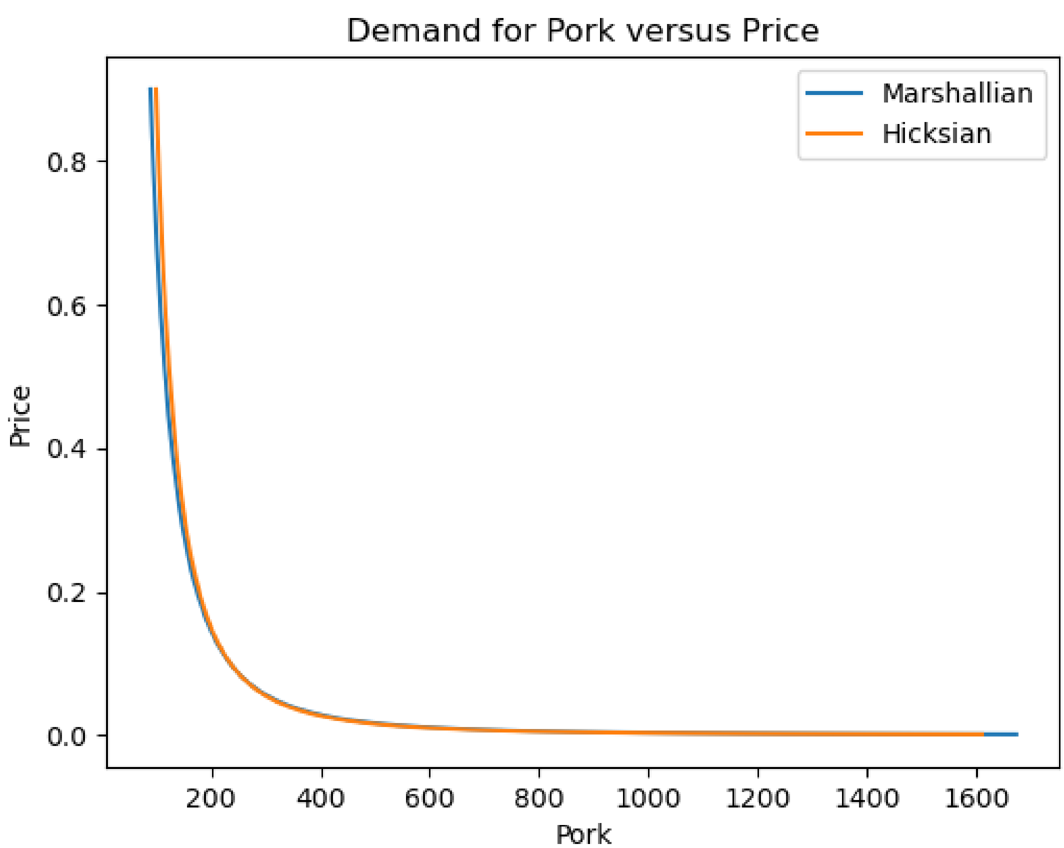
[76]:
```
# carbohydrate consumption
import plotly.express as px
carbo_consump = consumption('carbo')
carbo_consump.show()
```

1.1.2 Policy Costs

1.1.3 Marshallian vs. Hicksian Demand Curves

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

my_j = 'Pork'

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 Pork versus Price')
```



[80]:
```python
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)

    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')
```

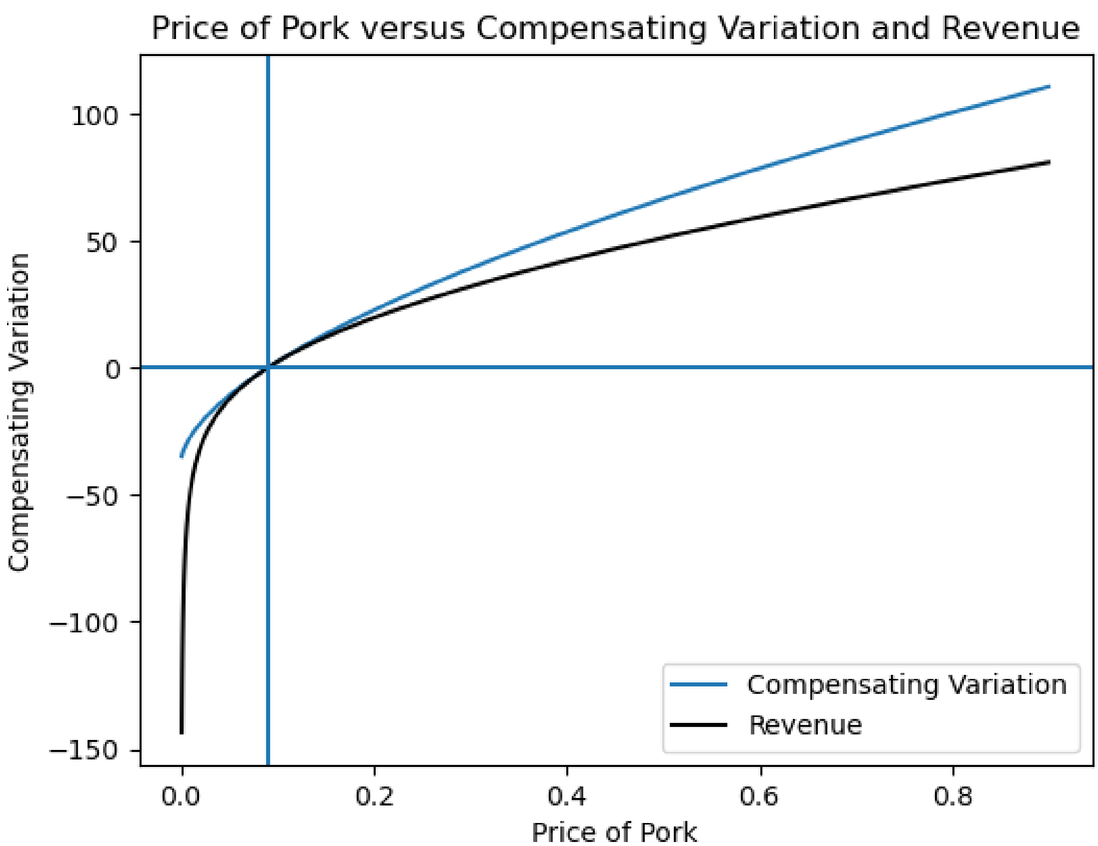
1.1.4 Price Changes, Revenue, and Compensating Variation

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

[81]:
```python
my_j = 'Pork'

fig, ax1 = plt.subplots()

ax1.plot(P,[compensating_variation(U0,pbar,my_prices(p0,j=my_j)) for p0 in P])
```

```
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')
ax1.legend(('Compensating Variation','Revenue'))
ax1.axhline(0)
ax1.axvline(pbar.loc[my_j])
ax1.set_title('Price of Pork versus Compensating Variation and Revenue')
```

[81]: Text(0.5, 1.0, 'Price of Pork 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:

[82]:
```
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)
```

[82]:
```
Text(0.5, 1.0, 'Price of Pork versus Deadweight Loss')
```