1 Introduction

According to OEC (The Observatory of Economic Complexity), coffee were around the world's 124th most traded products in 2021, with a total trade of 36 billion dollars. With such a huge amount of trading capacity, the producers retain 10% of the retail coffee price. With Many coffee products are produced in developing countries such as Brazil and Vietnam. As the coffee production procedures become more mature, these coffee products are sold with different labels in developed countries; the labels helps indicate sustainable or environmental friendly productions.

The research for labeling effects is quite important because it helps understand whether the coffee labels help with the consumption of sustainable products. Specifically, the paper considers three different labeling effect on coffee. The first label is Certified Bio label, which is designed to provide biobased information to consumers. Bio-based coffee is coffee that is produced using sustainable agricultural practices and is derived from renewable biomass sources, such as coffee plants. The second label is "Fair-Trade" label, which concerns the sustainability and the working envirnoment of coffee production. The Fairtrade label guarantees that products, such as coffee, tea, chocolate, and other commodities, are produced in a way that supports fair prices, living wages, and safe working conditions for farmers and workers in developing countries. The third label 'certified_wild' indicates whether the coffe is wildly grown. Mainly, wild grown coffee label indicates that coffee was grown in natural environment (rainforests) with none or little human internvention (perfect daily grind). In general, by assigning single or multiple labels to a coffee in the qustionnaire under a multiple setting, the research is able to investigate consumers' willingness to pay for different labels in a more complicated setting, where more than one labels can appear on a product.

There has been many past research on consumer demand for ethical product. However, most focus on one specific label. The effect of "fair trade" label is intensively studied. The piror research shows that labels usually positively influence consumers' willingness to pay for ethically sourced products. With the increasing number of labeling options available in the market, it is important to examine the effectiveness of different labels and how they interact with each other. This research uses data collected by choice experiment from 141 participants in Germany. By using a multiple label setting, this research aims to investigate consumers' decision making when multiple labels exist.

2 Literature Review

There are numerous research projects on consumer willingness to pay and labeling effects on various commodities like coffee, milk, candy, t-shirt. A survey in 1999 by the Program on International Policy Attitudes found out that around 75% of respondents indicated they were willing to pay 25 dollars for a 20 dollars garment that was certified as not being made in a sweatshop. Past research from National Bureau of Economic Research discovered that about 80% surveyed participants said they were willing to pay more for a product if labeled as good working environment.

Daniel Wikstrom did a choice experiment on willingness to pay for sustainable coffee. The research focuses on KARV-dertification and Fair-trade_certification. The study shows that individuals participate in non-profit organizations are more willing to pay for Fiar-trade labels. The questionnaire design is quite different from the one used in the paper. It presents two alternatives in each question and every participant must make a choice between the two. This research aims to suggest producers how they shoudl price coffee products and inclue different labels.

Another paper 'Consumer demand for fair trade: evidence from a multistore field experiment' revealed that some price-sensitive shoppers may be less willing to pay for the labels. In other words, there are large heterogeneity in consumer willingness to pay for ethical labels. Thus, in this research, it is useful to examine the model considering such heterogeneity through participants' income level. In general, most studies on consumers WTP show that consumers are willing to pay a price premium on labled coffee; however, the scale of such price premium is different across groups and depends on the specific context and coffee information.

This paper is different from the past research from mainly two aspects. First, most research on labelling effects aim to provide suugestions to firm-level marketing strategies based on ethical labels. However, this research focus on consumer decision making and intend to investigates the effectiveness of ethical labels to help with sustainable coffee production. Second, most past research took a frequentist approach which fail give useful information about how different groups of consumers can have WTP drawn from different posteriors. This study considers consumers within and among different income, education, age, and gender groups, and will discover the best model to discover the labeling effect and consumers WTP for different labels, allowing heterogeneity among consumers.

3 Data Source

All datat used are primary data colleced through a choice experiment. The data was collected under an experimental setting from 141 participants in Germany. Coffee has been very essential for German culture for over hundreds of years. While coffee shops and acfes ae popular, Germans also consume a grat amount of coffee at home. According to recent statistics, Germany ranks 11th globally in coffee consumption, with an average of 6.5 kilograms consumed per capita yearly. Thus, choosing the questionnaire based in Germany makes more since the coffee markets and labels are more established in Germany.

The questionnaire contains three types of questions: (1) personal coffee preferences and knowledge about existing lables (2) 6 questions about coffee choice for 18 different coffees with different labels, origins, and price for each coffee (3) personal education, age, and income information.

In [2]:

```
coffee = pd.read_csv('coffee_m.csv')
coffee.head()
```

Out[2]:

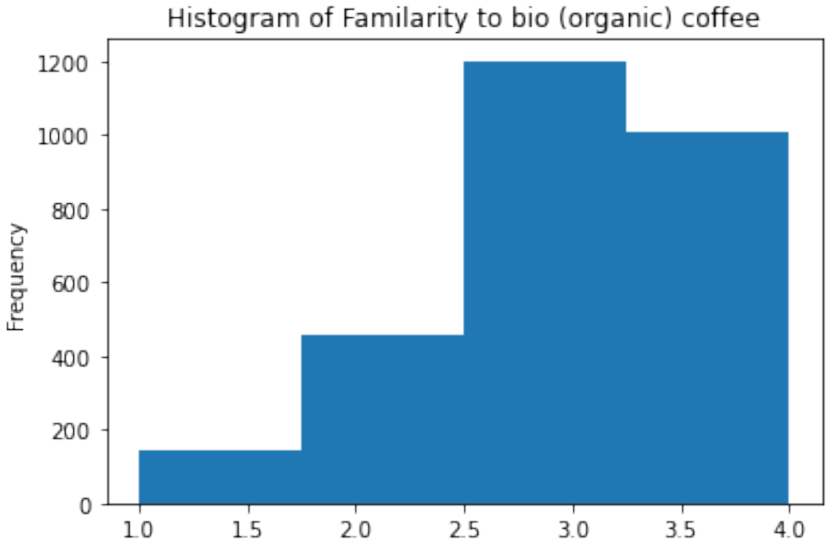
	index	certified_bio	certified_fair_trade	certified_wild	id	origin_brazil	origin_ethiopian
0	0	0	0	0	1	0	0
1	0	1	0	1	1	0	1
2	1	0	0	0	1	0	1
3	2	1	1	0	1	0	0
4	4	1	0	1	1	0	1

5 rows × 57 columns

Note: 1= not well known, 2= not known, 3= known, 4= well known

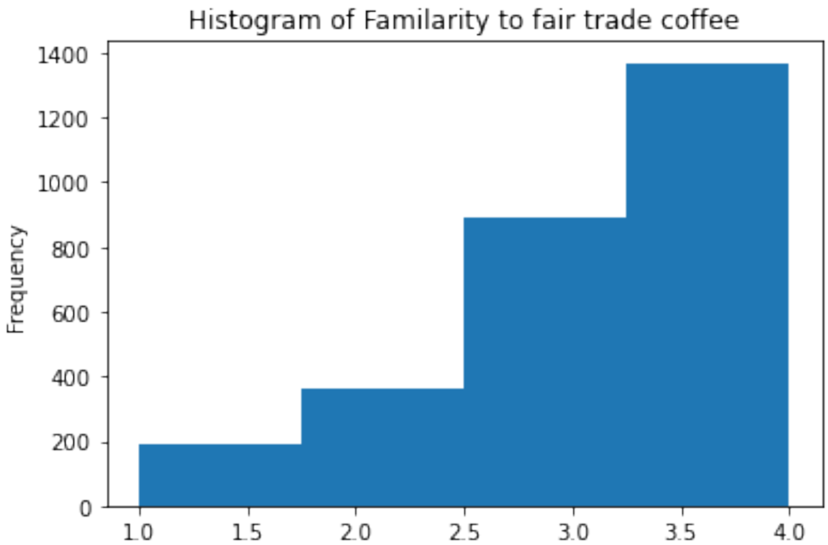
In [3]:
```
coffee['q2a'].plot.hist(bins = 4)
plt.title("Histogram of Familarity to bio (organic) coffee")
```

Out[3]:
```
Text(0.5, 1.0, 'Histogram of Familarity to bio (organic) coffee')
```



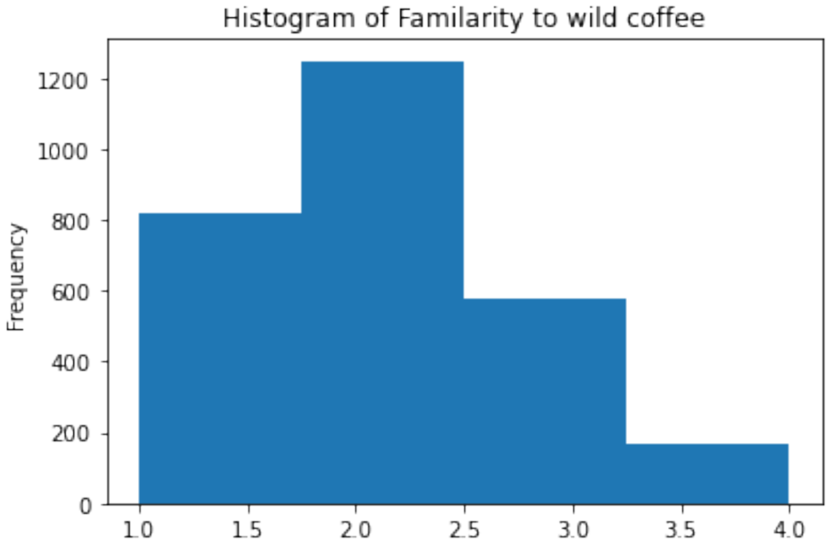
In [4]:
```
coffee['q2b'].plot.hist(bins = 4)
plt.title("Histogram of Familarity to fair trade coffee")
```

Out[4]:
```
Text(0.5, 1.0, 'Histogram of Familarity to fair trade coffee')
```



In [5]:
```
coffee['q2c'].plot.hist(bins = 4)
plt.title("Histogram of Familarity to wild coffee")
```

Out[5]:
```
Text(0.5, 1.0, 'Histogram of Familarity to wild coffee')
```



The three histograms above show to what extent are consumers familiar with the bio, fair trade, and wild labels. The histograms tell that most consumers are familiar with bio and fair trade labels while less are familiar with the wild grown label. Thus, we may expect a lower willingness to pay for wild labels.

4 Econometric Model

The coefficients on label dummies (Certified_BIO, Certified_Fair_Trade, Certified_wild) are the variable of interest. The utility function for a certain coffee k is:

$$V_k = \beta_{none}(OriginNone_k == 1) + \beta_{ethi}(Ethiopia_k == 1) + \beta_{braz}(Brazil_k == 1) + \\ + \beta_{fair}(FairTrade == 1) + \beta_{bio}(BIO_k == 1) + \beta_{wild}(Wild_k == 1) +$$

All variables that remain constant accross questions for an individual/ same ID will be eliminated when calculating the conditional logit likelihood. Thus, it does not make sense to include a constant term in the model.

Five models are considered and compared in this paper. The first four models are hierarchical models group by income, education, age, gender respectively. The last model is an pooled model. The consumer personal information (income, education, age, gender) are considered in the hierarchical models, which will captures the heterogeneity within different consumer groups. The result is sampled using Bayesian model, by taking a Monte Carlo Markov Chain of the posterior distribution. I assume Five models will be compared using WAIC criteria at last and choose the best fit model.

Note: I initially considered the two-way effects when multiple labels appear on one coffee. However, the sampling process takes too long and it is hard to run four hierarchical uncentered model. Thus, I only included single label effect below; the model considered two-way effect is specified as:

$$V_k = \beta_{none}(OriginNone_k == 1) + \beta_{ethi}(Ethiopia_k == 1) + \beta_{braz}(Brazil_k == 1) + \\ + \beta_{fair}(FairTrade == 1) + \beta_{bio}(BIO_k == 1) + \beta_{wild}(Wild_k == 1) \\ + \beta_{fair+bio}(FairTrade_k == 1)(BIO_k == 1) + \beta_{fair+wild}(FairTrade_k == 1)(Wil \\ + \beta_{bio+wild}(BIO_k == 1)(Wild_k == 1) + \epsilon_k$$

4.1 Variable Specification

1. Label dummies

- certified_bio: ==1 if the coffee has a certified_bio label
- certified_fair_trade: ==1 if the coffee has a certified_fair_trade label
- certified_wild: ==1 if the coffee has a certified_wild label

Note that a coffee choice can have more than one label.

2. Origin (Control variable)

- origin_brazil
- origin_ethiopian
- origin_none
- The other default origin is Columbia.

3. Dependent variable

- Choice (Probability)

4. Hierarchical model groups:

- income: annual household income. 0= below 5000, 1= 5000-15000, 2= 15000-30000, 3= 30000-50000, 5= over 50000
- education: highest degree, 0= high school, 2= Bachelor, 3= PhD, 4= Graduate degree, 5= other
- age: 0= 16 to 25, 1= 26 to 35, 2= 36 to 45, 3= 46 to 55, 5= over 55
- gender: 1= male, 0= female

All variables constant accross questions for an individual/ same ID will be eliminated when calculating the conditional logit likelihood. Thus, it does not make sense to include a constant term in the model. The prior and hyperprior are set as Normal and HalfCauchy. The normal priors centered at zero. The reason for choosing normal prior for mu is that coefficients on WTP for labels, origins, and price effect could be positive or negative.

4.2 Willingness to pay

To measure the willingness to pay, I refer to the marginal utility function. Thus, the WTP is calculated as

$$-\frac{\Delta\beta_{label_i}}{\Delta\beta_{price}}$$

that is, the change in label parameter divided by change in price parameter. We add the negative sign because as price increase, willingness to pay will decrease. WTP is only calculated in the pooled model and the best model under waic criteria.

In [6]:

```
# Create index:
rows_per_group = 4
# Calculate the number of groups
num_groups = len(coffee) // rows_per_group
# Create the index list
choice_index = np.array([i // rows_per_group for i in range(len
```

4.3.1 Model by income

In [7]:
```
with pm.Model() as hierarchical_model_income:


    # Hyperprior
    mu_bio = pm.Normal('mu_bio', mu=0., sigma=5)
    sigma_bio = pm.HalfCauchy('sigma_bio', beta=1)
    mu_ft = pm.Normal('mu_ft', mu=0., sigma=5)
    sigma_ft = pm.HalfCauchy('sigma_ft', beta=1)
    mu_wild = pm.Normal('mu_wild', mu=0., sigma=5)
    sigma_wild = pm.HalfCauchy('sigma_wild', beta=1)
    mu_p = pm.Normal('mu_p', mu=0., sigma=5)
    sigma_p = pm.HalfCauchy('sigma_p', beta=1)

    # Prior distributions for the parameters
    beta_none = pm.Normal('beta_none', mu=0., sigma=5.)
    beta_ethi = pm.Normal('beta_ethi', mu=0., sigma=5.)
    beta_braz = pm.Normal('beta_braz', mu=0., sigma=5.)

    #Colombia as standardized
    beta_bio_offset = pm.Normal('beta_bio_offset',mu = 0., sigm
    beta_bio = pm.Deterministic('beta_bio', mu_bio+sigma_bio*be

    beta_fair_offset = pm.Normal('beta_fair_offset',mu = 0., si
    beta_fair = pm.Deterministic('beta_fair', mu_ft+sigma_ft*be

    beta_wild_offset = pm.Normal('beta_wild_offset',mu = 0., si
    beta_wild = pm.Deterministic('beta_wild', mu_wild+sigma_wil

    beta_price_offset = pm.Normal('beta_price_offset',mu = 0.,
    beta_price = pm.Deterministic('beta_price', mu_p+sigma_p*be

    def loglike(choice, beta_braz, beta_ethi, beta_none, beta_b

        V = beta_braz*coffee['origin_brazil']+ beta_ethi*coffee
            +beta_bio[coffee.income] * coffee['certified_bio']
            coffee['certified_wild']+ beta_price[coffee.income]

        exp_v = T.exp(V)
        choice_exp_v = choice*exp_v

        denom = T.bincount(choice_index, weights = exp_v)
        num = T.bincount(choice_index, weights = choice_exp_v)

        prob = num/denom
        loglike = T.sum(T.log(prob))
        return loglike

    choice_like = pm.DensityDist('logit', beta_braz, beta_ethi,
                        beta_fair, beta_wild, beta_price, logp=logl
```

In [8]:
```
with hierarchical_model_income:
    income_hierarchical_trace = pm.sample(tune=6000, target_acc
```

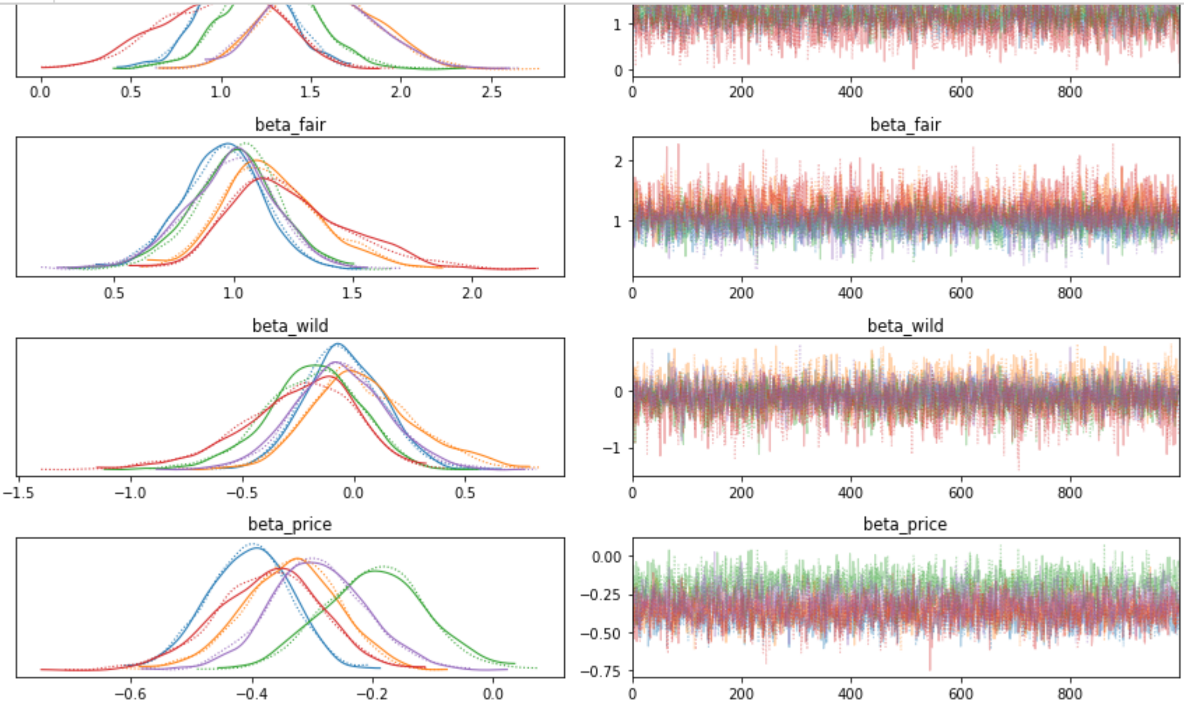
```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [mu_bio, sigma_bio, mu_ft, sigma_ft, mu_wild, sigma_wild, mu
_p, sigma_p, beta_none, beta_ethi, beta_braz, beta_bio_offset, bet
a_fair_offset, beta_wild_offset, beta_price_offset]
```

100.00% [14000/14000 05:38<00:00

Sampling 2 chains, 0 divergences]

```
Sampling 2 chains for 6_000 tune and 1_000 draw iterations (12_000
+ 2_000 draws total) took 339 seconds.
```

In [9]:
```
pm.plot_trace(income_hierarchical_trace);
plt.tight_layout()
```



In [10]:
```
#pm.summary(income_hierarchical_trace)
```

Notice: The summary and rhat are included at the end of the paper for space concern. They all show convergence in rhat.

4.3.2 Model by education

In [11]:

```
with pm.Model() as hierarchical_model_educ:

    # Hyperprior
    mu_bio = pm.Normal('mu_bio', mu=0., sigma=5)
```

```
    sigma_bio = pm.HalfCauchy('sigma_bio', beta=1)
    mu_ft = pm.Normal('mu_ft', mu=0., sigma=5)
    sigma_ft = pm.HalfCauchy('sigma_ft', beta=1)
    mu_wild = pm.Normal('mu_wild', mu=0., sigma=5)
    sigma_wild = pm.HalfCauchy('sigma_wild', beta=1)
    mu_p = pm.Normal('mu_p', mu=0., sigma=5)
    sigma_p = pm.HalfCauchy('sigma_p', beta=1)

    # Prior distributions for the parameters
    # intercept = pm.Normal('intercept', mu=0., sigma=10.)  # i
    beta_none = pm.Normal('beta_none', mu=0., sigma=5.)
    beta_ethi = pm.Normal('beta_ethi', mu=0., sigma=5.)
    beta_braz = pm.Normal('beta_braz', mu=0., sigma=5.)


    #Colombia as standardized
    beta_bio_offset = pm.Normal('beta_bio_offset',mu = 0., sigm
    beta_bio = pm.Deterministic('beta_bio', mu_bio+sigma_bio*be

    beta_fair_offset = pm.Normal('beta_fair_offset',mu = 0., si
    beta_fair = pm.Deterministic('beta_fair', mu_ft+sigma_ft*be

    beta_wild_offset = pm.Normal('beta_wild_offset',mu = 0., si
    beta_wild = pm.Deterministic('beta_wild', mu_wild+sigma_wil

    beta_price_offset = pm.Normal('beta_price_offset',mu = 0., 
    beta_price = pm.Deterministic('beta_price', mu_p+sigma_p*be

    def loglike(choice, beta_braz, beta_ethi, beta_none, beta_b

        V = beta_braz*coffee['origin_brazil']+ beta_ethi*coffee
            +beta_bio[coffee.edu] * coffee['certified_bio'] + b
            coffee['certified_wild']+ beta_price[coffee.edu] *

        exp_v = T.exp(V)
        choice_exp_v = choice*exp_v

        denom = T.bincount(choice_index, weights = exp_v)
        num = T.bincount(choice_index, weights = choice_exp_v)

        prob = num/denom
        loglike = T.sum(T.log(prob))
        return loglike

    choice_like = pm.DensityDist('logit', beta_braz, beta_ethi,
                    beta_fair, beta_wild, beta_price, logp=logl
```

In [16]:
```
with hierarchical_model_educ:
    educ_hierarchical_trace = pm.sample(tune=6000, target_accep
```

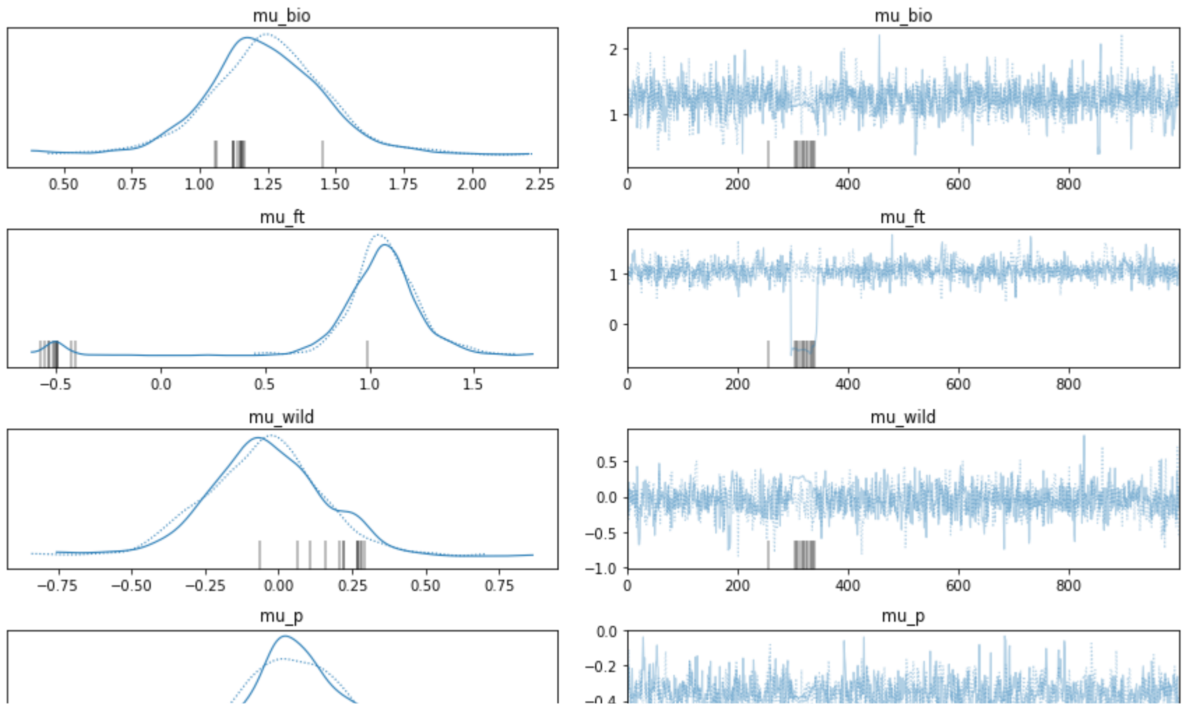
```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [mu_bio, sigma_bio, mu_ft, sigma_ft, mu_wild, sigma_wild, mu
_p, sigma_p, beta_none, beta_ethi, beta_braz, beta_bio_offset, bet
a_fair_offset, beta_wild_offset, beta_price_offset]
```

100.00% [14000/14000 05:30<00:00

Sampling 2 chains, 13 divergences]

```
Sampling 2 chains for 6_000 tune and 1_000 draw iterations (12_000
+ 2_000 draws total) took 331 seconds.
There were 13 divergences after tuning. Increase `target_accept` o
r reparameterize.
The acceptance probability does not match the target. It is 0.9063
, but should be close to 0.95. Try to increase the number of tunin
g steps.
```

In [17]:
```
pm.plot_trace(educ_hierarchical_trace);
plt.tight_layout()
```



4.3.3 Model by age

In [18]:
```
with pm.Model() as hierarchical_model_age:

    # Hyperprior
    mu_bio = pm.Normal('mu_bio', mu=0., sigma=5)
    sigma_bio = pm.HalfCauchy('sigma_bio', beta=1)
    mu_ft = pm.Normal('mu_ft', mu=0., sigma=5)
    sigma_ft = pm.HalfCauchy('sigma_ft', beta=1)
    mu_wild = pm.Normal('mu_wild', mu=0., sigma=5)
    sigma_wild = pm.HalfCauchy('sigma_wild', beta=1)
    mu_p = pm.Normal('mu_p', mu=0., sigma=5)
    sigma_p = pm.HalfCauchy('sigma_p', beta=1)

    # Prior distributions for the parameters
    # intercept = pm.Normal('intercept', mu=0., sigma=10.)  # i
    beta_none = pm.Normal('beta_none', mu=0., sigma=5.)
    beta_ethi = pm.Normal('beta_ethi', mu=0., sigma=5.)
    beta_braz = pm.Normal('beta_braz', mu=0., sigma=5.)

    #Colombia as standardized
    beta_bio_offset = pm.Normal('beta_bio_offset',mu = 0., sigm
    beta_bio = pm.Deterministic('beta_bio', mu_bio+sigma_bio*be

    beta_fair_offset = pm.Normal('beta_fair_offset',mu = 0., si
    beta_fair = pm.Deterministic('beta_fair', mu_ft+sigma_ft*be

    beta_wild_offset = pm.Normal('beta_wild_offset',mu = 0., si
    beta_wild = pm.Deterministic('beta_wild', mu_wild+sigma_wil

    beta_price_offset = pm.Normal('beta_price_offset',mu = 0.,
    beta_price = pm.Deterministic('beta_price', mu_p+sigma_p*be

    def loglike(choice, beta_braz, beta_ethi, beta_none, beta_b

        V = beta_braz*coffee['origin_brazil']+ beta_ethi*coffee
            +beta_bio[coffee.age] * coffee['certified_bio'] + b
            coffee['certified_wild']+ beta_price[coffee.age] *

        exp_v = T.exp(V)
        choice_exp_v = choice*exp_v

        denom = T.bincount(choice_index, weights = exp_v)
        num = T.bincount(choice_index, weights = choice_exp_v)

        prob = num/denom
        loglike = T.sum(T.log(prob))
        return loglike

    choice_like = pm.DensityDist('logit', beta_braz, beta_ethi,
                        beta_fair, beta_wild, beta_price, logp=logl
```

In [19]:
```
with hierarchical_model_age:
    age_hierarchical_trace = pm.sample(tune=6000, target_accept
```

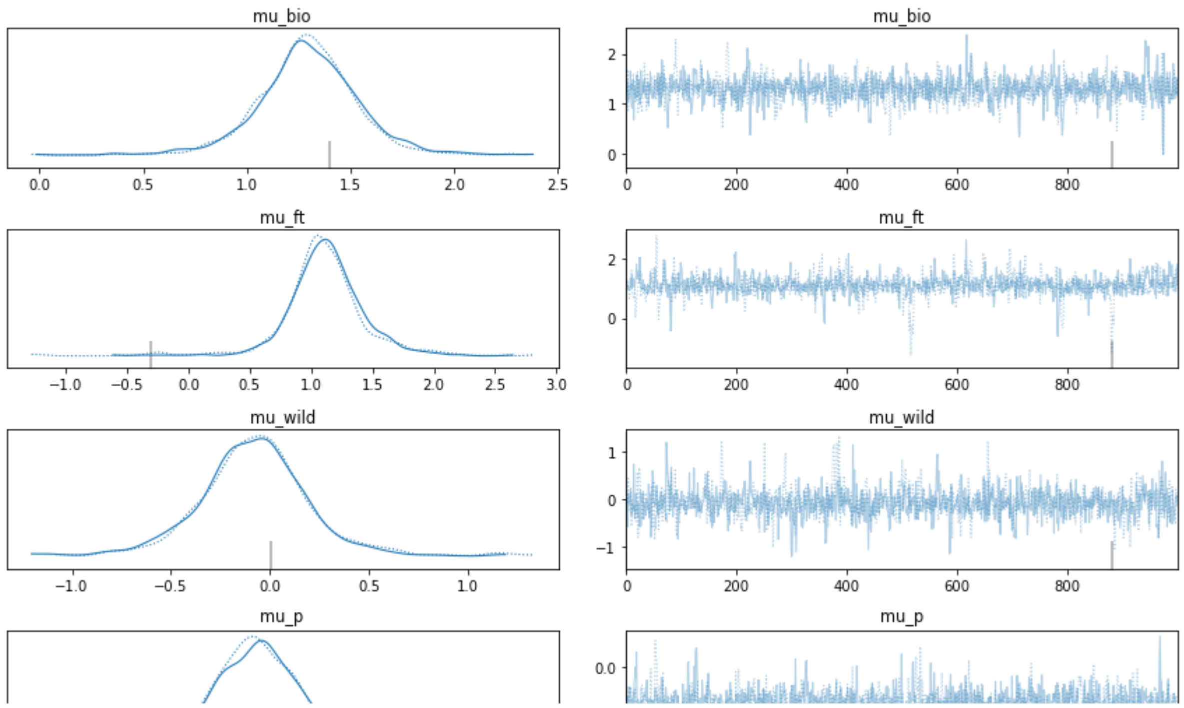
```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [mu_bio, sigma_bio, mu_ft, sigma_ft, mu_wild, sigma_wild, mu
_p, sigma_p, beta_none, beta_ethi, beta_braz, beta_bio_offset, bet
a_fair_offset, beta_wild_offset, beta_price_offset]
```

100.00% [14000/14000 06:41<00:00

Sampling 2 chains, 1 divergences]

```
Sampling 2 chains for 6_000 tune and 1_000 draw iterations (12_000
+ 2_000 draws total) took 402 seconds.
There was 1 divergence after tuning. Increase `target_accept` or r
eparameterize.
```

In [20]:
```
pm.plot_trace(age_hierarchical_trace);
plt.tight_layout()
```



4.3.4 Model by gender

In [21]:

```
coffee['gender'] = coffee['q15']
coffee.head()
# ==1 if is male
```

Out[21]:

	index	certified_bio	certified_fair_trade	certified_wild	id	origin_brazil	origin_ethiopian
0	0	0	0	0	1	0	0
1	0	1	0	1	1	0	1
2	1	0	0	0	1	0	1
3	2	1	1	0	1	0	0
4	4	1	0	1	1	0	1

5 rows × 58 columns

In [22]:
```
with pm.Model() as hierarchical_model_gender:

    # Hyperprior
    mu_bio = pm.Normal('mu_bio', mu=0., sigma=5)
    sigma_bio = pm.HalfCauchy('sigma_bio', beta=1)
    mu_ft = pm.Normal('mu_ft', mu=0., sigma=5)
    sigma_ft = pm.HalfCauchy('sigma_ft', beta=1)
    mu_wild = pm.Normal('mu_wild', mu=0., sigma=5)
    sigma_wild = pm.HalfCauchy('sigma_wild', beta=1)
    mu_p = pm.Normal('mu_p', mu=0., sigma=5)
    sigma_p = pm.HalfCauchy('sigma_p', beta=1)


    # Prior distributions for the parameters
    # intercept = pm.Normal('intercept', mu=0., sigma=10.)  # i
    beta_none = pm.Normal('beta_none', mu=0., sigma=5.)
    beta_ethi = pm.Normal('beta_ethi', mu=0., sigma=5.)
    beta_braz = pm.Normal('beta_braz', mu=0., sigma=5.)

    #Colombia as standardized
    beta_bio_offset = pm.Normal('beta_bio_offset',mu = 0., sigm
    beta_bio = pm.Deterministic('beta_bio', mu_bio+sigma_bio*be

    beta_fair_offset = pm.Normal('beta_fair_offset',mu = 0., si
    beta_fair = pm.Deterministic('beta_fair', mu_ft+sigma_ft*be

    beta_wild_offset = pm.Normal('beta_wild_offset',mu = 0., si
    beta_wild = pm.Deterministic('beta_wild', mu_wild+sigma_wil

    beta_price_offset = pm.Normal('beta_price_offset',mu = 0.,
    beta_price = pm.Deterministic('beta_price', mu_p+sigma_p*be


    def loglike(choice, beta_braz, beta_ethi, beta_none, beta_b

        V = beta_braz*coffee['origin_brazil']+ beta_ethi*coffee
            +beta_bio[coffee.gender] * coffee['certified_bio']
            coffee['certified_wild']+beta_price[coffee.gender]

        exp_v = T.exp(V)
        choice_exp_v = choice*exp_v

        denom = T.bincount(choice_index, weights = exp_v)
        num = T.bincount(choice_index, weights = choice_exp_v)

        prob = num/denom
        loglike = T.sum(T.log(prob))
        return loglike

    choice_like = pm.DensityDist('logit', beta_braz, beta_ethi,
                        beta_fair, beta_wild, beta_price, logp=logl
```

In [23]:
```
with hierarchical_model_gender:
    gender_hierarchical_trace = pm.sample(tune=6000, target_acc
```

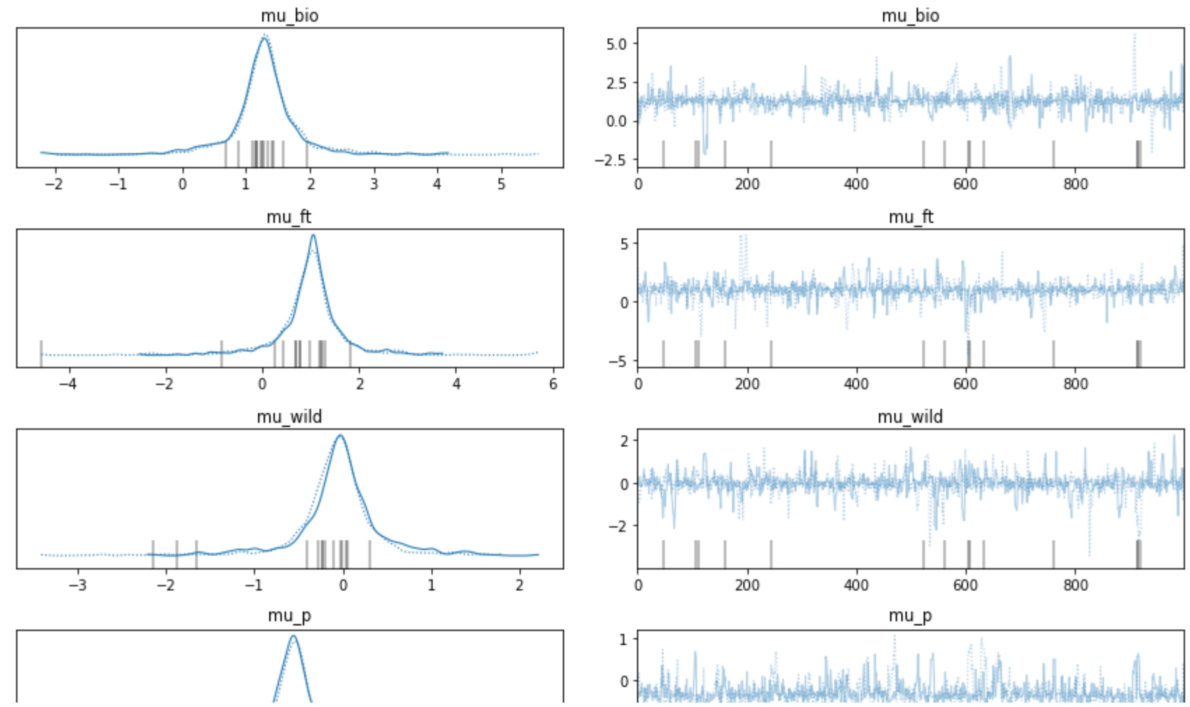
```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [mu_bio, sigma_bio, mu_ft, sigma_ft, mu_wild, sigma_wild, mu
_p, sigma_p, beta_none, beta_ethi, beta_braz, beta_bio_offset, bet
a_fair_offset, beta_wild_offset, beta_price_offset]
```

100.00% [14000/14000 20:14<00:00

Sampling 2 chains, 14 divergences]

```
Sampling 2 chains for 6_000 tune and 1_000 draw iterations (12_000
+ 2_000 draws total) took 1215 seconds.
There were 6 divergences after tuning. Increase `target_accept` or
reparameterize.
There were 8 divergences after tuning. Increase `target_accept` or
reparameterize.
```

In [24]:
```
pm.plot_trace(gender_hierarchical_trace);
plt.tight_layout()
```



4.3.5 Pooled model

In [25]:

```
with pm.Model() as model:

    # Prior distributions for the parameters
    # intercept = pm.Normal('intercept', mu=0., sigma=10.)  # i
    beta_ethi = pm.Normal('beta_ethi', mu=0., sigma=5.)
    beta_braz = pm.Normal('beta_braz', mu=0., sigma=5.)
    beta_none = pm.Normal('beta_none', mu=0., sigma=5.)
    #Colombia as standardized
    beta_bio = pm.Normal('beta_bio', mu=0., sigma=5.)
    beta_fair = pm.Normal('beta_fair', mu=0., sigma=5.)
    beta_wild = pm.Normal('beta_wild', mu=0., sigma=5.)
    beta_price = pm.Normal('beta_price', mu=0., sigma=5.)

    WTP_bio = pm.Deterministic('WTP_bio', -beta_bio / beta_pric
    WTP_ft = pm.Deterministic('WTP_ft', -beta_fair / beta_price
    WTP_wild = pm.Deterministic('WTP_wild', -beta_wild / beta_p

    def loglike(choice, beta_braz, beta_ethi, beta_none, beta_b
        V = beta_braz*coffee['origin_brazil']+ beta_ethi*coffee
            +beta_bio*coffee['certified_bio'] + beta_fair* coff
            coffee['certified_wild']+ beta_price* coffee['price

        exp_v = T.exp(V)
        choice_exp_v = choice*exp_v
        denom = T.bincount(choice_index, weights = exp_v)
        num = T.bincount(choice_index, weights = choice_exp_v)

        prob = num/denom
        loglike = T.sum(T.log(prob))
        return loglike

    choice_like = pm.DensityDist('logit', beta_braz, beta_ethi,
                        beta_fair, beta_wild, beta_price, logp=logl
```

In [26]:

```
with model:
    pooled_trace = pm.sample(tune=6000, target_accept=.95, retu
```

```
Auto-assigning NUTS sampler...
Initializing NUTS using jitter+adapt_diag...
Multiprocess sampling (2 chains in 2 jobs)
NUTS: [beta_ethi, beta_braz, beta_none, beta_bio, beta_fair, beta_
wild, beta_price]
```

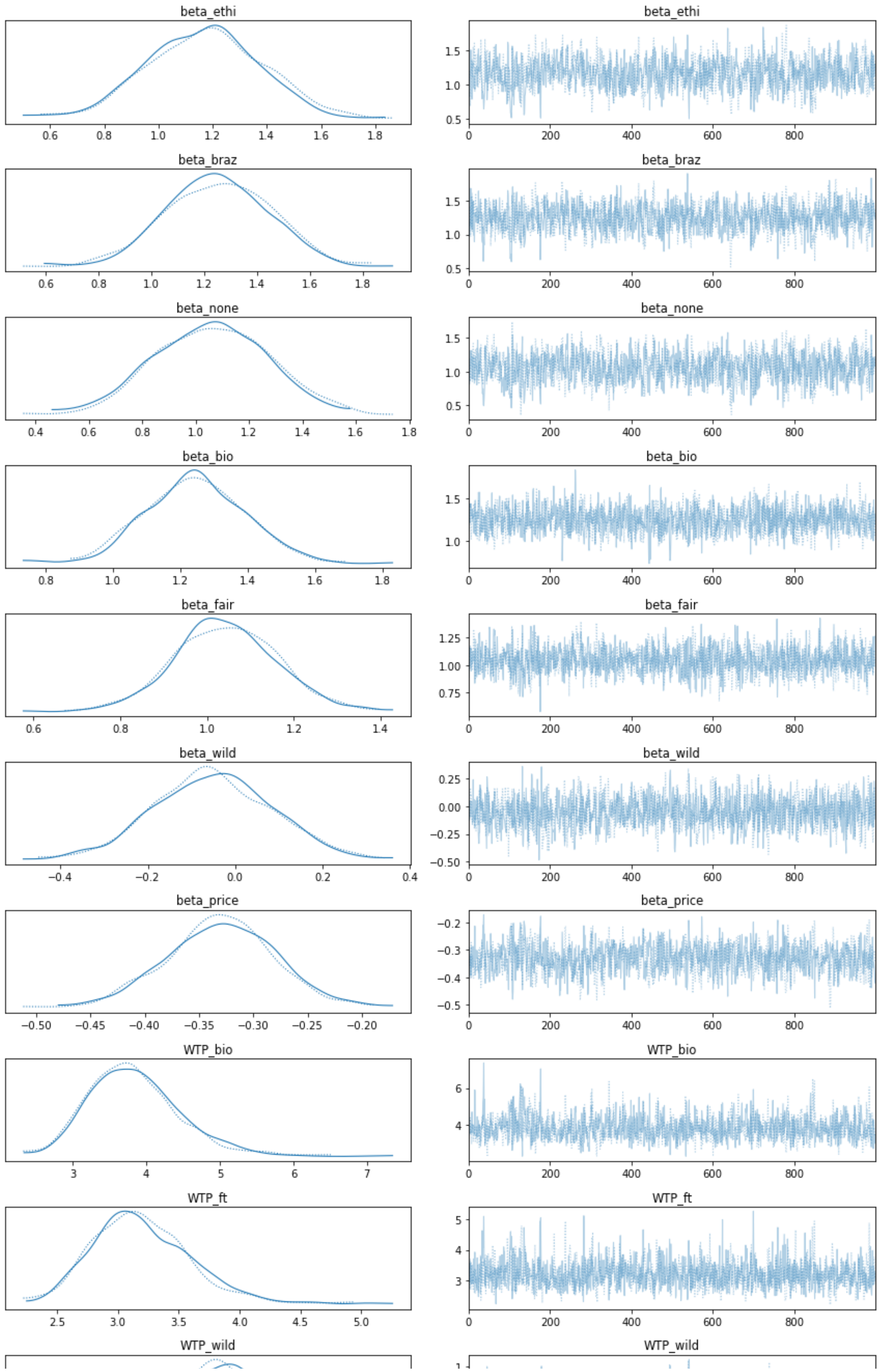
100.00% [14000/14000 01:20<00:00

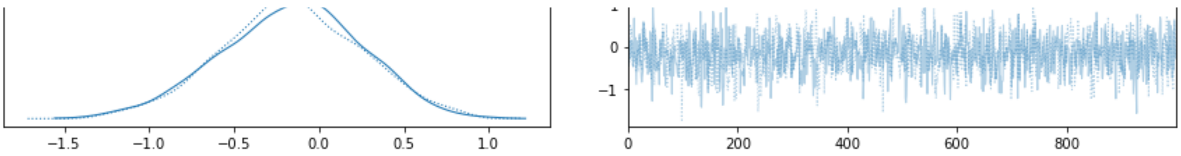
Sampling 2 chains, 0 divergences]

```
Sampling 2 chains for 6_000 tune and 1_000 draw iterations (12_000
+ 2_000 draws total) took 80 seconds.
```

In [27]:

```
pm.plot_trace(pooled_trace);
plt.tight_layout()
```





In [ ]:

```
 
```

5 Result & discussion

5.1 Convergence discussion

All traces show convergence with rhat around 1.0. Before applying 'uncentered' approach to the hierarchical models, there are divergences in the centered model. The reason is the heterogeneity within posterior isn't that significant for wild_label. Thue, using uncentered model will avoid tunning and divergences. The rhat of each model is shown below.

5.1.1 income hierarchical model

In [28]:

```
pm.summary(income_hierarchical_trace)
```

Out[28]:

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_
mu_bio	1.294	0.283	0.759	1.803	0.010	0.007	1036.0	96
mu_ft	1.061	0.191	0.693	1.403	0.006	0.004	1103.0	61
mu_wild	-0.101	0.204	-0.500	0.251	0.005	0.004	1778.0	94
mu_p	-0.319	0.092	-0.479	-0.155	0.003	0.002	1020.0	75
beta_none	1.087	0.214	0.661	1.459	0.006	0.004	1326.0	147
beta_ethi	1.205	0.213	0.811	1.592	0.006	0.004	1350.0	132
beta_braz	1.275	0.204	0.888	1.642	0.005	0.003	1757.0	145
beta_bio_offset[0]	-0.440	0.716	-1.831	0.835	0.022	0.016	1053.0	112
beta_bio_offset[1]	0.620	0.784	-0.991	2.058	0.021	0.015	1450.0	156
beta_bio_offset[2]	-0.053	0.718	-1.383	1.309	0.018	0.015	1571.0	160
beta_bio_offset[3]	-0.711	0.777	-2.112	0.732	0.024	0.017	1051.0	108
beta_bio_offset[4]	0.590	0.764	-0.853	2.102	0.023	0.016	1135.0	115
beta_fair_offset[0]	-0.425	0.808	-1.931	1.174	0.021	0.016	1439.0	137
beta_fair_offset[1]	0.340	0.833	-1.338	1.780	0.019	0.016	1806.0	163
beta_fair_offset[2]	-0.198	0.813	-1.719	1.336	0.021	0.017	1547.0	140

beta_fair_offset[3]	0.576	0.890	-1.161	2.246	0.021	0.019	1834.0	152
beta_fair_offset[4]	-0.266	0.845	-1.760	1.359	0.021	0.020	1638.0	137
beta_wild_offset[0]	0.206	0.791	-1.297	1.692	0.020	0.017	1616.0	103
beta_wild_offset[1]	0.475	0.873	-1.179	2.041	0.022	0.017	1637.0	139
beta_wild_offset[2]	-0.310	0.847	-1.929	1.305	0.020	0.018	1890.0	129
beta_wild_offset[3]	-0.490	0.874	-2.255	1.056	0.024	0.019	1320.0	133
beta_wild_offset[4]	0.148	0.832	-1.448	1.673	0.019	0.019	1925.0	122
beta_price_offset[0]	-0.689	0.669	-1.957	0.567	0.019	0.014	1237.0	139
beta_price_offset[1]	-0.114	0.695	-1.512	1.140	0.019	0.015	1290.0	139
beta_price_offset[2]	0.972	0.714	-0.257	2.348	0.020	0.014	1270.0	98
beta_price_offset[3]	-0.368	0.717	-1.629	1.021	0.019	0.015	1417.0	132
beta_price_offset[4]	0.210	0.709	-1.162	1.507	0.018	0.015	1576.0	137
sigma_bio	0.430	0.314	0.000	0.935	0.012	0.009	602.0	61
sigma_ft	0.262	0.228	0.000	0.658	0.009	0.006	610.0	92
sigma_wild	0.258	0.225	0.000	0.638	0.008	0.005	745.0	105
sigma_p	0.147	0.102	0.004	0.324	0.004	0.003	686.0	98
beta_bio[0]	1.134	0.214	0.742	1.540	0.005	0.004	1651.0	172
beta_bio[1]	1.555	0.284	1.068	2.104	0.008	0.006	1295.0	136
beta_bio[2]	1.275	0.245	0.857	1.780	0.005	0.004	2095.0	175
beta_bio[3]	0.997	0.316	0.420	1.552	0.009	0.007	1107.0	141
beta_bio[4]	1.549	0.284	1.029	2.058	0.008	0.006	1337.0	155
beta_fair[0]	0.951	0.170	0.622	1.262	0.004	0.003	1701.0	166
beta_fair[1]	1.160	0.210	0.799	1.581	0.006	0.004	1406.0	158
beta_fair[2]	1.007	0.182	0.629	1.329	0.004	0.003	1681.0	169
beta_fair[3]	1.234	0.254	0.808	1.725	0.007	0.005	1349.0	149
beta_fair[4]	0.985	0.198	0.592	1.338	0.004	0.003	2111.0	170
beta_wild[0]	-0.045	0.176	-0.374	0.287	0.004	0.003	2083.0	145
beta_wild[1]	0.042	0.238	-0.362	0.522	0.006	0.004	1679.0	170
beta_wild[2]	-0.184	0.214	-0.576	0.228	0.005	0.004	2136.0	141
beta_wild[3]	-0.254	0.258	-0.764	0.199	0.007	0.005	1363.0	170
beta_wild[4]	-0.058	0.211	-0.476	0.316	0.005	0.004	2146.0	155
beta_price[0]	-0.405	0.068	-0.530	-0.277	0.002	0.001	1488.0	176
beta_price[1]	-0.336	0.078	-0.487	-0.195	0.002	0.001	1790.0	160
beta_price[2]	-0.197	0.085	-0.349	-0.035	0.002	0.002	1264.0	155

beta_price[3]	-0.372	0.088	-0.551	-0.221	0.002	0.002	1579.0	172
beta_price[4]	-0.291	0.080	-0.443	-0.136	0.002	0.001	1867.0	137

5.1.2 education hierarchical model

In [29]:
```
pm.summary(educ_hierarchical_trace)
```

Out[29]:

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_
mu_bio	1.243	0.221	0.826	1.657	0.007	0.005	1141.0	102
mu_ft	1.033	0.286	0.743	1.458	0.037	0.027	240.0	8
mu_wild	-0.049	0.200	-0.417	0.316	0.006	0.005	1045.0	104
mu_p	-0.359	0.088	-0.527	-0.187	0.003	0.002	871.0	111
beta_none	1.100	0.209	0.712	1.491	0.006	0.004	1429.0	142
beta_ethi	1.220	0.206	0.877	1.625	0.008	0.005	735.0	146
beta_braz	1.287	0.195	0.957	1.658	0.006	0.004	992.0	126
beta_bio_offset[0]	0.095	0.889	-1.645	1.777	0.048	0.040	442.0	11
beta_bio_offset[1]	0.302	0.788	-1.144	1.811	0.021	0.017	1428.0	136
beta_bio_offset[2]	-0.336	0.845	-1.929	1.268	0.020	0.018	1819.0	155
beta_bio_offset[3]	0.391	0.970	-1.445	2.322	0.055	0.039	402.0	10

5.1.3 age hierarchical model

In [30]:
```
pm.summary(age_hierarchical_trace)
```

Out[30]:

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_
mu_bio	1.293	0.245	0.851	1.774	0.008	0.006	1109.0	85
mu_ft	1.109	0.338	0.567	1.770	0.013	0.009	805.0	73
mu_wild	-0.078	0.291	-0.671	0.445	0.010	0.007	1028.0	92
mu_p	-0.292	0.106	-0.502	-0.105	0.003	0.002	1033.0	93
beta_none	1.122	0.213	0.728	1.513	0.006	0.004	1478.0	165
beta_ethi	1.215	0.211	0.837	1.627	0.006	0.004	1376.0	147
beta_braz	1.299	0.207	0.903	1.692	0.005	0.004	1498.0	139
beta_bio_offset[0]	-0.125	0.790	-1.673	1.325	0.019	0.017	1788.0	143
beta_bio_offset[1]	0.173	0.840	-1.305	1.844	0.018	0.018	2091.0	133
beta_bio_offset[2]	0.017	0.922	-1.749	1.666	0.022	0.023	1799.0	110

beta_bio_offset[3]	-0.486	0.860	-2.010	1.195	0.020	0.017	1828.0	155
beta_bio_offset[4]	0.559	0.907	-1.204	2.199	0.023	0.018	1564.0	127
beta_fair_offset[0]	0.150	0.695	-1.149	1.467	0.019	0.018	1391.0	118
beta_fair_offset[1]	-0.704	0.691	-1.962	0.611	0.020	0.014	1250.0	108
beta_fair_offset[2]	1.084	0.804	-0.402	2.606	0.021	0.015	1474.0	92
beta_fair_offset[3]	-0.242	0.682	-1.610	0.957	0.018	0.014	1383.0	143
beta_fair_offset[4]	-0.240	0.693	-1.602	1.041	0.019	0.016	1289.0	114
beta_wild_offset[0]	0.322	0.685	-1.002	1.568	0.019	0.015	1349.0	119
beta_wild_offset[1]	-0.157	0.730	-1.539	1.243	0.019	0.016	1524.0	148
beta_wild_offset[2]	0.199	0.815	-1.321	1.735	0.020	0.018	1661.0	139
beta_wild_offset[3]	0.646	0.737	-0.704	2.085	0.019	0.014	1542.0	133
beta_wild_offset[4]	-0.979	0.801	-2.480	0.461	0.021	0.015	1511.0	123
beta_price_offset[0]	-0.983	0.668	-2.169	0.267	0.019	0.014	1156.0	108
beta_price_offset[1]	-0.419	0.646	-1.558	0.825	0.017	0.014	1365.0	127
beta_price_offset[2]	0.234	0.726	-1.094	1.660	0.018	0.015	1572.0	163
beta_price_offset[3]	0.565	0.654	-0.666	1.797	0.017	0.012	1539.0	135
beta_price_offset[4]	0.568	0.654	-0.573	1.894	0.018	0.013	1372.0	128
sigma_bio	0.314	0.266	0.000	0.780	0.011	0.008	578.0	93
sigma_ft	0.532	0.403	0.002	1.182	0.017	0.012	437.0	74
sigma_wild	0.428	0.303	0.000	0.910	0.011	0.008	615.0	70
sigma_p	0.185	0.112	0.024	0.382	0.004	0.003	864.0	111
beta_bio[0]	1.257	0.186	0.921	1.613	0.004	0.003	2328.0	165
beta_bio[1]	1.355	0.245	0.845	1.782	0.005	0.004	2062.0	154
beta_bio[2]	1.300	0.333	0.687	1.987	0.008	0.006	1801.0	152
beta_bio[3]	1.114	0.284	0.578	1.608	0.008	0.006	1176.0	174
beta_bio[4]	1.503	0.296	1.002	2.095	0.009	0.006	1024.0	175
beta_fair[0]	1.165	0.179	0.810	1.484	0.004	0.003	1620.0	152
beta_fair[1]	0.782	0.233	0.393	1.250	0.007	0.005	1081.0	141
beta_fair[2]	1.683	0.464	0.862	2.485	0.017	0.012	675.0	136
beta_fair[3]	0.998	0.229	0.565	1.430	0.005	0.003	2290.0	183
beta_fair[4]	1.000	0.221	0.576	1.415	0.005	0.004	1913.0	152
beta_wild[0]	0.038	0.178	-0.299	0.356	0.004	0.003	2075.0	178
beta_wild[1]	-0.140	0.230	-0.561	0.308	0.005	0.004	2442.0	155
beta_wild[2]	0.008	0.325	-0.658	0.606	0.007	0.006	2051.0	171

beta_wild[3]	0.183	0.266	-0.267	0.718	0.007	0.005	1309.0	185
beta_wild[4]	-0.479	0.313	-1.025	0.115	0.010	0.007	948.0	135
beta_price[0]	-0.443	0.066	-0.567	-0.316	0.002	0.001	1630.0	161
beta_price[1]	-0.360	0.080	-0.503	-0.200	0.002	0.001	1623.0	181
beta_price[2]	-0.252	0.119	-0.468	-0.020	0.003	0.002	1496.0	153
beta_price[3]	-0.206	0.084	-0.362	-0.039	0.002	0.001	1969.0	158
beta_price[4]	-0.206	0.084	-0.378	-0.060	0.002	0.001	2155.0	178

5.1.4 gender hierarchical model

In [31]:
```
pm.summary(gender_hierarchical_trace)
```

Out[31]:

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_
mu_bio	1.292	0.574	0.115	2.279	0.024	0.017	726.0	61
mu_ft	0.999	0.751	-0.519	2.503	0.029	0.021	838.0	67
mu_wild	-0.052	0.481	-0.970	1.039	0.020	0.015	689.0	50
mu_p	-0.315	0.308	-1.023	0.333	0.016	0.011	453.0	37
beta_none	1.054	0.213	0.627	1.430	0.008	0.006	753.0	118
beta_ethi	1.179	0.211	0.796	1.598	0.007	0.005	821.0	97
beta_braz	1.267	0.206	0.897	1.654	0.007	0.005	932.0	98
beta_bio_offset[0]	-0.273	0.817	-1.809	1.259	0.025	0.018	1031.0	118
beta_bio_offset[1]	0.210	0.830	-1.356	1.719	0.025	0.018	1111.0	118
beta_fair_offset[0]	0.441	0.767	-0.886	1.991	0.022	0.016	1208.0	110
beta_fair_offset[1]	-0.439	0.806	-1.972	1.029	0.024	0.017	1093.0	110
beta_wild_offset[0]	-0.015	0.813	-1.376	1.708	0.026	0.018	978.0	126
beta_wild_offset[1]	0.041	0.837	-1.469	1.645	0.026	0.019	1004.0	113
beta_price_offset[0]	0.102	0.753	-1.345	1.418	0.025	0.018	882.0	126
beta_price_offset[1]	-0.207	0.764	-1.649	1.228	0.025	0.018	897.0	134
sigma_bio	0.583	0.722	0.000	1.725	0.025	0.017	772.0	83
sigma_ft	0.840	1.018	0.000	2.261	0.045	0.032	696.0	64
sigma_wild	0.491	0.623	0.000	1.440	0.021	0.015	736.0	98
sigma_p	0.372	0.439	0.000	1.242	0.018	0.013	581.0	73
beta_bio[0]	1.188	0.174	0.870	1.520	0.004	0.003	2033.0	153
beta_bio[1]	1.363	0.200	0.990	1.720	0.004	0.003	1988.0	184
beta_fair[0]	1.225	0.153	0.933	1.506	0.004	0.002	1882.0	115
beta_fair[1]	0.797	0.177	0.485	1.142	0.004	0.003	1713.0	125
beta_wild[0]	-0.059	0.157	-0.370	0.224	0.003	0.003	2383.0	190
beta_wild[1]	-0.032	0.169	-0.337	0.307	0.004	0.003	2087.0	177
beta_price[0]	-0.316	0.056	-0.422	-0.214	0.002	0.001	1131.0	117
beta_price[1]	-0.365	0.064	-0.483	-0.253	0.002	0.001	1195.0	152

5.1.5 pooled model

In [32]:
```
pm.summary(pooled_trace)
```

Out[32]:

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_ha
beta_ethi	1.168	0.209	0.806	1.563	0.008	0.005	760.0	958.0	1.
beta_braz	1.252	0.199	0.870	1.598	0.006	0.004	1065.0	1016.0	1.
beta_none	1.059	0.211	0.644	1.426	0.007	0.005	879.0	951.0	1.
beta_bio	1.245	0.145	0.984	1.514	0.004	0.003	1521.0	1202.0	1.
beta_fair	1.044	0.117	0.832	1.275	0.003	0.002	1554.0	1298.0	1.
beta_wild	-0.051	0.134	-0.286	0.219	0.004	0.003	1439.0	1370.0	1.
beta_price	-0.330	0.051	-0.428	-0.239	0.002	0.001	955.0	1009.0	1.
WTP_bio	3.838	0.627	2.784	5.053	0.019	0.014	1085.0	1254.0	1.
WTP_ft	3.205	0.423	2.522	4.056	0.012	0.008	1358.0	1251.0	1.
WTP_wild	-0.166	0.425	-1.009	0.585	0.011	0.009	1431.0	1387.0	1.

5.2 Model selection

Using WAIC (Widely Applicable Information Criterion), we compare the 5 models above.

In [33]:
```
pm.compare({'hierarchical_model_income':income_hierarchical_tra
```

```
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1661:
UserWarning: For one or more samples the posterior variance of the
log predictive densities exceeds 0.4. This could be indication of
WAIC starting to fail.
See http://arxiv.org/abs/1507.04544
(http://arxiv.org/abs/1507.04544) for details
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1677:
UserWarning: The point-wise WAIC is the same with the sum WAIC, pl
ease double check
            the Observed RV in your model to make sure it returns
element-wise logp.

  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1661:
UserWarning: For one or more samples the posterior variance of the
log predictive densities exceeds 0.4. This could be indication of
WAIC starting to fail.
See http://arxiv.org/abs/1507.04544
(http://arxiv.org/abs/1507.04544) for details
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1677:
UserWarning: The point-wise WAIC is the same with the sum WAIC, pl
ease double check
            the Observed RV in your model to make sure it returns
```

```
element-wise logp.

  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1661:
UserWarning: For one or more samples the posterior variance of the
log predictive densities exceeds 0.4. This could be indication of
WAIC starting to fail.
See http://arxiv.org/abs/1507.04544
(http://arxiv.org/abs/1507.04544) for details
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1677:
UserWarning: The point-wise WAIC is the same with the sum WAIC, pl
ease double check
            the Observed RV in your model to make sure it returns
element-wise logp.

  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1661:
UserWarning: For one or more samples the posterior variance of the
log predictive densities exceeds 0.4. This could be indication of
WAIC starting to fail.
See http://arxiv.org/abs/1507.04544
(http://arxiv.org/abs/1507.04544) for details
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1677:
UserWarning: The point-wise WAIC is the same with the sum WAIC, pl
ease double check
            the Observed RV in your model to make sure it returns
element-wise logp.

  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1661:
UserWarning: For one or more samples the posterior variance of the
log predictive densities exceeds 0.4. This could be indication of
WAIC starting to fail.
See http://arxiv.org/abs/1507.04544
(http://arxiv.org/abs/1507.04544) for details
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:1677:
UserWarning: The point-wise WAIC is the same with the sum WAIC, pl
ease double check
            the Observed RV in your model to make sure it returns
element-wise logp.

  warnings.warn(
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:247:
RuntimeWarning: divide by zero encountered in log
  score += np.log(np.dot(exp_ic_i[i], w_full))
/opt/conda/lib/python3.10/site-packages/arviz/stats/stats.py:255:
RuntimeWarning: invalid value encountered in double_scalars
  grad[k] += (exp_ic_i[i, k] - exp_ic_i[i, km1]) / np.dot(exp_ic_i
[i], w_full)
```

Out[33]:

	rank	waic	p_waic	d_waic	weight	se	dse	warı

hierarchical_model_income	0	-832.186227	9.266539	0.000000	0.2	0.0	0.0
hierarchical_model_age	1	-834.116508	12.899299	1.930281	0.2	0.0	0.0
hierarchical_model_educ	2	-837.559858	7.305566	5.373630	0.2	0.0	0.0
hierarchical_model_gender	3	-840.601955	5.104810	8.415728	0.2	0.0	0.0
model	4	-842.471745	3.237999	10.285517	0.2	0.0	0.0

The preferred model is the hierarchical model by income, with the greatest waic value among the 5 proposed models. The first three models have very similar waic values (-832.765 (by income)>-834.137 (by age)>-834.917 (by education)). The pooled model has the worst waic value, since it fails to capture heterogeneity among consumers. We will look at and compare results from the the hierarchical_model_income and pooled model.

5.3 General results

In general, labeling effects on fair trade labels and bio labels are positive. We can observe that for every income, education, age, gender group, the parameter on fair trade label and the parameter for bio label are positive, while the parameter on wild label is around zero or even negative. This could be caused by the lack of knowledge for wild label as discussed in the beginning.

5.3 Hierarchical models

Best model based on waic:

- Hierarchical income: The hierarchical model by income has the highest waic value. We can observe that the group of people with the highest income level aren't necessarily the group that has the highest parameter for each label. However, the is a general increasing trend in the parameter for labels when income increaes. The heterogeneity for different income groups are more pronounce when it comes to parameter for bio leabel, comparing to fair trade label. The coefficient on income[0] group regarding bio label has a mean of 0.9 while for income[4] group, the mean is around 1.5. It makes sense because organic food is regarded as a healthy lifestyle for people with higher income. Additionally, people with higher income are less sensitive to price change as the income[4] group has a mean on price equals to -0.3 while income[0] group has a mean on price equals to -0.4. There is a noticeable heterogeneity across different income groups.

  The trace with WTP for income hierarchical model is shown in the appendix. income group 2 and 4 have the highest WTP for bio labels (around WTP_bio = 5 to 6), compares to WTP_bio = 3.8 in the pooled model; income group 2 has the highest WTP for fair trade labels (around WTP_ft = 3.6 to 5), compares to WTP_ft = 3.2 in the pooled model. There are unignorable heterogeneity within consumers; dispersion for bio_labels among consumers' WTP is greater than that of the fair trade_labels. It is also worth noticing that WTP relates to both label recognition and price sensitivity, which explains why the WTP for different income groups cannot be easily predicted. Notice that the method of calculating WTP for a hierarchical may not be ideal and can be improved if there are more time. The results for WTP are differ slightly each time; the standard deviation on posterior is very large somteims. A possible solution is to take log values in future studies.

Interesting findings:

- Hierarchical gender: Hierarchical model by gender does not have a great waic value; it was in fact only slightly better than the pooled model. However, the posterior provides an interesting discovery. The parameter on fair trade coffee differs greatly between male and female. male has a posterior mean around 0.8 while female has a posterior mean around 1.2. This suggests that females pay more attention to social labels.

Other models also show heterogeneity for WTP (which can be implicitly deduced from label coefficients and price coefficients).

6 Conclusion

The primary objective of this paper is to examine consumers' willingness to pay for various labels. The findings reveal several key insights. Firstly, it is observed that consumers exhibit a higher willingness to pay for the bio label compared to the fair trade label, and both of these labels have a higher willingness to pay compared to the wild label. Interestingly, the wild label does not seem to enjoy significant popularity among consumers.

Secondly, the study identifies substantial heterogeneity among consumers. By grouping consumers based on income, it is found that this categorization aligns well with the observed data and prior expectations. Surprisingly, consumers with higher income do not necessarily exhibit the highest willingness to pay for labels. The willingness to pay for labels is influenced by two factors: the recognition of a specific label (as captured by the parameter on label dummies) and price sensitivity (as indicated by the parameter on price).

Among the different models considered, the income hierarchical model performs the best based on the waic test. However, it is worth noting that the waic values are also relatively close when considering alternative groupings such as age or education. Therefore, exploring the willingness to pay results across different age and education groups would be valuable. Although the explicit calculation of willingness to pay is not provided for all models, it can be reasonably inferred that heterogeneity exists among consumers when they are grouped according to different characteristics, as reflected by the label parameters. Overall, these findings underscore the importance of considering consumers' willingness to pay for labels and the presence of heterogeneity within consumer preferences, highlighting the influence of label recognition and price sensitivity. Obviously, the wild label is less popular than the other two labels.

There are certain limitations to this study that should be acknowledged. Firstly, the study does not provide a detailed analysis of the willingness to pay (WTP) for each hierarchical model. While the coefficients on the label variables can serve as an approximate reference for WTP, they may not provide precise estimates. Nevertheless, these coefficients can still be utilized to compare the WTP for different labels. Secondly, the study does not examine the potential two-way effects or interactions between labels. Exploring the interactions between various labels could offer valuable insights into how consumers' preferences and WTP might be influenced when multiple labels are present simultaneously. Thirdly, if we can collect data from more regions (other countries), we can view this issue from the geometric aspects. Addressing these limitations would enhance the comprehensiveness of the analysis and provide a more nuanced understanding of consumers' WTP for different labels.

7 Reference

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codes are based on 'hierarchical_models' ipynb file from class.

8 Appendix

WTP for hierarchical income model

In [34]:

```python
with pm.Model() as hierarchical_model_income:


    # Hyperprior
    mu_bio = pm.Normal('mu_bio', mu=0., sigma=5)
    sigma_bio = pm.HalfCauchy('sigma_bio', beta=1)
    mu_ft = pm.Normal('mu_ft', mu=0., sigma=5)
    sigma_ft = pm.HalfCauchy('sigma_ft', beta=1)
    mu_wild = pm.Normal('mu_wild', mu=0., sigma=5)
    sigma_wild = pm.HalfCauchy('sigma_wild', beta=1)
    mu_p = pm.Normal('mu_p', mu=0., sigma=5)
    sigma_p = pm.HalfCauchy('sigma_p', beta=1)

    # Prior distributions for the parameters
    beta_none = pm.Normal('beta_none', mu=0., sigma=5.)
    beta_ethi = pm.Normal('beta_ethi', mu=0., sigma=5.)
    beta_braz = pm.Normal('beta_braz', mu=0., sigma=5.)

    #Colombia as standardized
    beta_bio_offset = pm.Normal('beta_bio_offset',mu = 0., sigm
    beta_bio = pm.Deterministic('beta_bio', mu_bio+sigma_bio*be
```

```
    beta_bio = pm.Deterministic('beta_bio', mu_bio+sigma_bio*be

    beta_fair_offset = pm.Normal('beta_fair_offset',mu = 0., si
    beta_fair = pm.Deterministic('beta_fair', mu_ft+sigma_ft*be

    beta_wild_offset = pm.Normal('beta_wild_offset',mu = 0., si
    beta_wild = pm.Deterministic('beta_wild', mu_wild+sigma_wil

    beta_price_offset = pm.Normal('beta_price_offset',mu = 0.,
    beta_price = pm.Deterministic('beta_price', mu_p+sigma_p*be


    WTP_bio0 = pm.Deterministic('WTP_bio0', -beta_bio[0]/beta_p
    WTP_bio1 = pm.Deterministic('WTP_bio1', -beta_bio[1]/beta_p
    WTP_bio2 = pm.Deterministic('WTP_bio2', -beta_bio[2]/beta_p
    WTP_bio3 = pm.Deterministic('WTP_bio3', -beta_bio[3]/beta_p
    WTP_bio4 = pm.Deterministic('WTP_bio4', -beta_bio[4]/beta_p

    WTP_ft0 = pm.Deterministic('WTP_ft0', -beta_fair[0]/beta_pr
    WTP_ft1 = pm.Deterministic('WTP_ft1', -beta_fair[1]/beta_pr
    WTP_ft2 = pm.Deterministic('WTP_ft2', -beta_fair[2]/beta_pr
    WTP_ft3 = pm.Deterministic('WTP_ft3', -beta_fair[3]/beta_pr
    WTP_ft4 = pm.Deterministic('WTP_ft4', -beta_fair[4]/beta_pr

    WTP_wild0 = pm.Deterministic('WTP_wild0', -beta_wild[0]/bet
    WTP_wild1 = pm.Deterministic('WTP_wild1', -beta_wild[1]/bet
    WTP_wild2 = pm.Deterministic('WTP_wild2', -beta_wild[2]/bet
    WTP_wild3 = pm.Deterministic('WTP_wild3', -beta_wild[3]/bet
    WTP_wild4 = pm.Deterministic('WTP_wild4', -beta_wild[4]/bet


    def loglike(choice, beta_braz, beta_ethi, beta_none, beta_b

        V = beta_braz*coffee['origin_brazil']+ beta_ethi*coffee
            +beta_bio[coffee.income] * coffee['certified_bio']
            coffee['certified_wild']+ beta_price[coffee.income]

        exp_v = T.exp(V)
        choice_exp_v = choice*exp_v

        denom = T.bincount(choice_index, weights = exp_v)
        num = T.bincount(choice_index, weights = choice_exp_v)

        prob = num/denom
        loglike = T.sum(T.log(prob))
        return loglike

    choice_like = pm.DensityDist('logit', beta_braz, beta_ethi,
                        beta_fair, beta_wild, beta_price, logp=logl
```