

blp

February 22, 2025

Henrique de Souza Passos

```
[452]: get_ipython().magic('reset -sf')
```

```
/tmp/ipykernel_548659/3674724974.py:1: DeprecationWarning: `magic(...)` is
deprecated since IPython 0.13 (warning added in 8.1), use
run_line_magic(magic_name, parameter_s).
  get_ipython().magic('reset -sf')
```

```
[453]: from IPython import get_ipython
import scipy.io
import numpy as np
import pandas as pd
import scipy.stats as stats
import pyblp
import statsmodels.api as sm
from itertools import product
from linearmodels.iv import IV2SLS
```

1 1. Setting

A number of national producers sell substitute products in regional markets. The government intends to bail out a struggling firm and allow it to merge with one of its healthy competitors. What do you expect the welfare consequences to be?

No curto prazo isso pode evitar um aumento de preços devido a injeção de liquidez que o governo poderia fazer. No entanto, no longo prazo, poderia haver maior concentração de mercado aumentando os preços para os consumidores.

2 2. Data description

For the empirical exercise, we are giving you data on $T = 10$ markets. In these markets, 11 different firms sell a total of $J = 247$ products. All of the products are unique, so none of them are offered in multiple markets. The dataset is simulated, but you can still think of a product as a passenger vehicle with a set of characteristics if you like, although the units do not have an interpretation. The dataset contains the following pieces of data, where products are ordered by market (1-10): - “prodsMarket”: T -vector of the number of products in each market - “share”: J -vector of market shares - “f”: J -vector denoting the firm that sells the product - “ch”: $J \times 4$ -matrix of constant and three product characteristics - “pr”: J -vector of prices - “costShifters”: $J \times 2$ -matrix of cost shifters

3. Basic summary statistics

1. Prepare a table with the following pieces of information for each market: How many firms are active? How many products do they market in total? What fraction of agents bought one of the goods in the sample period?

```
[454]: mat_data = scipy.io.loadmat("/home/hspassos/mestrado/industrial/demand_data.
      ↪mat")

prodsMarket = {'market': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]}
prodsMarket = pd.DataFrame(prodsMarket)
prodsMarket['prodsMarket'] = mat_data['prodsMarket'].flatten()

# Criar tabela com os dados por produto
data = pd.DataFrame({
    'market_ids': 1 + np.repeat(np.arange(len(prodsMarket)),
    ↪prodsMarket['prodsMarket']),
    'firm_ids': mat_data['f'].flatten(),
    'shares': mat_data['share'].flatten(),
    'prices': mat_data['pr'].flatten(),
    'const': mat_data['ch'][:, 0],
    'char1': mat_data['ch'][:, 1],
    'char2': mat_data['ch'][:, 2],
    'char3': mat_data['ch'][:, 3],
    'costsh1': mat_data['costShifters'][:, 0],
    'costsh2': mat_data['costShifters'][:, 1],
})

data
```

```
[454]:
```

	market_ids	firm_ids	shares	prices	const	char1	char2	\
0	1	1	0.002115	4.775915	1.0	2.750983	0.672526	
1	1	9	0.032741	3.388449	1.0	1.022277	2.476778	
2	1	9	0.009585	4.085734	1.0	2.667053	0.760962	
3	1	7	0.024101	2.432229	1.0	1.068635	0.910503	
4	1	2	0.012206	4.486977	1.0	2.138262	1.871875	
..	
242	10	2	0.006462	4.524368	1.0	3.006674	0.118876	
243	10	10	0.002214	4.118809	1.0	1.125124	1.748192	
244	10	3	0.103526	2.840987	1.0	2.284540	0.467589	
245	10	11	0.003856	4.967610	1.0	2.869888	0.569319	
246	10	3	0.002055	3.674037	1.0	0.933852	1.152601	
	char3	costsh1	costsh2					
0	2.139236	0.158296	0.264869					
1	2.685004	0.479222	0.151009					
2	1.980984	0.276290	0.002862					

```

3    0.036386  0.109393  0.108614
4    3.655649  0.064100  0.468338
..      ...      ...      ...
242  1.877790  0.480930  0.039359
243  1.067760  0.483401  0.003548
244  1.036729  0.018995  0.136472
245  2.678046  0.252503  0.184921
246  0.341722  0.326308  0.474412

```

[247 rows x 10 columns]

2. Prepare a table with summary statistics for market share, characteristics, price, and cost shifters. Please include mean, median, minimum, maximum, and standard deviation. You can inspect these statistics separately for each market, but in what you report, you may pool all markets.

```

[455]: statistics = pd.DataFrame({
    'mean': data.iloc[:, 2:].mean(),
    'median': data.iloc[:, 2:].median(),
    'minimum': data.iloc[:, 2:].min(),
    'maximum': data.iloc[:, 2:].max(),
    'standard deviation': data.iloc[:, 2:].std()
}).T

statistics

```

```

[455]:
          shares  prices  const  char1  char2  char3 \
mean          0.024299  3.501501    1.0  1.473991  1.498017  1.472444
median         0.009474  3.520012    1.0  1.425105  1.451934  1.482724
minimum        0.000124  1.296677    1.0 -1.166353 -1.147205 -1.387708
maximum        0.268831  6.212918    1.0  4.362983  3.936271  4.482867
standard deviation  0.038427  0.828860    0.0  0.967242  0.913044  0.985834

          costsh1  costsh2
mean          0.264297  0.238784
median         0.272270  0.236695
minimum        0.005698  0.002097
maximum        0.499834  0.499676
standard deviation  0.140623  0.139543

```

4 4. Pure logit model

1. Suppose agents have the following utility function, where i denotes the agent, and j denotes the product:

$$u_{ij} = \frac{\delta_j}{x_j' \beta - \alpha_{pj} + \xi} + \epsilon_{ij}$$

where ϵ_{ij} is an iid error following a standard Type-I Extreme Value distribution with $F(\epsilon) = e^{-e^{-\epsilon}}$ (“logit” errors). Suppose further that the firms know ξ when setting prices but did not know ξ when setting characteristics.

1.a. What statistical assumptions can you make based on this? Which of your conditions, based on data provided to you, identify the parameter vector of interest, $\theta = (\alpha; \beta)$? In other words, what are valid (and relevant) instruments? Is the model over-identified?

Como ξ só é observado depois de definir os preços, ξ é endógeno em relação ao preço mas não em relação às características dos produtos. Como existe exogeneidade, um modelo OLS seria viesado, por isso é preciso usar instrumentos para estimar o preço.

1.b. Show how you can invert market shares to obtain the mean utility level δ_j for each product.

```
[456]: data_s0 = (
    data.groupby('market_ids')['shares'].sum().reset_index()
    .assign(s0=lambda x: 1 - x['shares'])
    [['market_ids', 's0']]
)

data_delta = (
    data.merge(data_s0, on='market_ids', how='left')
    .assign(delta=lambda x: np.log(x['shares']) - np.log(x['s0']))
)
```

1.c. Estimate $\theta = (\alpha; \beta)$ and provide standard errors for your estimate. You can try different combinations of instruments, but please use all the different types of instruments that are included or can be constructed from the data (i.e., “BLP instruments”).

```
[457]: data_delta["log_shares"] = np.log(data_delta["shares"]) - np.
    ↪log(data_delta["s0"])
data_delta['firm_ids'] = data_delta['firm_ids'].astype('category')
data_delta['market_ids'] = data_delta['market_ids'].astype('category')
data_delta['char_sum'] = data_delta[['char1', 'char2', 'char3']].sum(axis=1)
market_sums = data_delta.groupby('market_ids')['char_sum'].transform('sum')
data_delta['blp_iv'] = (market_sums - data_delta['char_sum']) / (data_delta.
    ↪groupby('market_ids')['char_sum'].transform('count') - 1)
firm_sums = data_delta.groupby('firm_ids')['prices'].transform('sum')
data_delta['hausman_iv'] = (firm_sums - data_delta['prices']) / (data_delta.
    ↪groupby('market_ids')['prices'].transform('count') - 1)

formula = "log_shares ~ char1 + char2 + char3 + [prices ~ blp_iv + costsh1 +
    ↪costsh2 + hausman_iv]"

# Estimar o modelo IV-2SLS (IV-Logit)
logit = IV2SLS.from_formula(formula, data=data_delta).fit(cov_type="robust")

# Exibir os resultados
```

```
print(logit.first_stage)
```

```
First Stage Estimation Results
=====
                                prices
-----
R-squared                      0.9796
Partial R-squared              0.1166
Shea's R-squared              0.1166
Partial F-statistic           33.078
P-value (Partial F-stat)      1.151e-06
Partial F-stat Distn          chi2(4)
=====
char1                          1.0791
                                (8.4259)
char2                          0.8022
                                (5.7481)
char3                          -0.0259
                                (-0.2977)
blp_iv                         0.0575
                                (0.8559)
costsh1                        1.0038
                                (4.3869)
costsh2                        0.6137
                                (2.4982)
hausman_iv                     0.0235
                                (1.3949)
-----
```

T-stats reported in parentheses

T-stats use same covariance type as original model

```
/tmp/ipykernel_548659/327344337.py:5: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
```

```
market_sums = data_delta.groupby('market_ids')['char_sum'].transform('sum')
```

```
/tmp/ipykernel_548659/327344337.py:6: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
```

```
data_delta['blp_iv'] = (market_sums - data_delta['char_sum']) /
(data_delta.groupby('market_ids')['char_sum'].transform('count') - 1)
```

```
/tmp/ipykernel_548659/327344337.py:7: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
```

```
firm_sums = data_delta.groupby('firm_ids')['prices'].transform('sum')
```

/tmp/ipykernel_548659/327344337.py:8: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.

```
data_delta['hausman_iv'] = (firm_sums - data_delta['prices']) /
(data_delta.groupby('market_ids')['prices'].transform('count') - 1)
```

[458]: `print(logit.summary)`

```

IV-2SLS Estimation Summary
=====
Dep. Variable:          log_shares    R-squared:                0.9868
Estimator:              IV-2SLS      Adj. R-squared:          0.9866
No. Observations:      247          F-statistic:             1.685e+04
Date:                  Sat, Feb 22 2025  P-value (F-stat)        0.0000
Time:                  19:29:01         Distribution:            chi2(4)
Cov. Estimator:        robust

```

```

Parameter Estimates
=====

```

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
char1	1.4340	0.2149	6.6718	0.0000	1.0128	1.8553
char2	1.0847	0.1800	6.0273	0.0000	0.7320	1.4374
char3	0.3763	0.0525	7.1737	0.0000	0.2735	0.4791
prices	-2.2472	0.1511	-14.875	0.0000	-2.5433	-1.9511

```

=====

```

```

Endogenous: prices
Instruments: blp_iv, costsh1, costsh2, hausman_iv
Robust Covariance (Heteroskedastic)
Debiased: False

```

```
[ ]: #usando o pyblp

logit_formulation = pyblp.Formulation('prices + blp_iv + hausman_iv + costsh1 +_
↪costsh2', absorb='C(market_ids)')
problem = pyblp.Problem(logit_formulation, data_delta)

logit_results = problem.solve()
```

```

Initializing the problem ...
Absorbing demand-side fixed effects ...
Initialized the problem after 00:00:00.

```

```

Dimensions:
=====
T    N    F    K1    MD    ED
---  ---  ---  ---  ---  ---

```

```

10  247  11   5   4   1
=====

```

Formulations:

```

=====
      Column Indices:      0      1      2      3      4
-----
X1: Linear Characteristics prices blp_iv hausman_iv costsh1 costsh2
=====

```

Solving the problem ...

Updating the weighting matrix ...

Computed results after 00:00:00.

Problem Results Summary:

```

=====
GMM      Objective      Clipped      Weighting Matrix
Step      Value          Shares      Condition Number
-----
  1  +6.3923106496717E-29    0      +6.9542689411171E+01
=====

```

Estimating standard errors ...

Computed results after 00:00:00.

Problem Results Summary:

```

=====
GMM      Objective      Clipped      Weighting Matrix      Covariance Matrix
Step      Value          Shares      Condition Number      Condition Number
-----
  2  +3.9990103661963E-29    0      +6.4100425113730E+01  +1.3703000719903E+17
=====

```

Cumulative Statistics:

```

=====
Computation  Objective
  Time      Evaluations
-----
  00:00:00      2
=====

```

Beta Estimates (Robust SEs in Parentheses):

```

=====
=====
      prices      blp_iv      hausman_iv
costsh1      costsh2
-----
-1.8674218370110E-01  -4.5342786153905E-01  -7.5194045607994E-02

```

```

-2.4337402093752E+00    -1.4264892232218E+00
(+1.5953975300724E-01)  (+1.2184238598572E-01)  (+1.2722296852473E-01)
(+6.3526567371086E-01)  (+6.6413984761463E-01)
=====
=====

```

The model may be under-identified. The total number of unfixed parameters is 5, which is more than the total number of moments, 4. Consider checking whether instruments were properly specified when initializing the problem, and whether parameters were properly configured when solving the problem.

2. Estimate and present the matrix of cross- and own-price elasticities for market 10 based on your model and parameter estimates.

```

[460]: elasticities = logit_results.compute_elasticities()
elasticities_market_10 = pd.DataFrame(elasticities[data.market_ids == 10])
elasticities_market_10 = elasticities_market_10.dropna(axis=1, how='all')

print(elasticities_market_10)

```

Computing elasticities with respect to prices ...
Finished after 00:00:00.

	0	1	2	3	4	5	6	\
0	-0.551264	0.085959	0.011161	0.005541	0.035728	0.030416	0.005459	
1	0.009565	-0.497555	0.011161	0.005541	0.035728	0.030416	0.005459	
2	0.009565	0.085959	-0.759001	0.005541	0.035728	0.030416	0.005459	
3	0.009565	0.085959	0.011161	-0.521117	0.035728	0.030416	0.005459	
4	0.009565	0.085959	0.011161	0.005541	-0.644579	0.030416	0.005459	
5	0.009565	0.085959	0.011161	0.005541	0.035728	-0.442167	0.005459	
6	0.009565	0.085959	0.011161	0.005541	0.035728	0.030416	-0.839431	
7	0.009565	0.085959	0.011161	0.005541	0.035728	0.030416	0.005459	
8	0.009565	0.085959	0.011161	0.005541	0.035728	0.030416	0.005459	
9	0.009565	0.085959	0.011161	0.005541	0.035728	0.030416	0.005459	
10	0.009565	0.085959	0.011161	0.005541	0.035728	0.030416	0.005459	

	7	8	9	10
0	0.001703	0.054924	0.003577	0.001410
1	0.001703	0.054924	0.003577	0.001410
2	0.001703	0.054924	0.003577	0.001410
3	0.001703	0.054924	0.003577	0.001410
4	0.001703	0.054924	0.003577	0.001410
5	0.001703	0.054924	0.003577	0.001410
6	0.001703	0.054924	0.003577	0.001410
7	-0.767453	0.054924	0.003577	0.001410
8	0.001703	-0.475608	0.003577	0.001410
9	0.001703	0.054924	-0.924085	0.001410
10	0.001703	0.054924	0.003577	-0.684688

3. In the next question, we are going to free up the substitution pattern by introducing random

coefficients as in BLP. Alternatively, we could think about implementing nested logit, the pure characteristics model, or multinomial probit. Would they be appealing in this setting? Why or why not?

Para usar o modelo de características puras seria necessário ter os dados da demanda que não estão disponíveis. O modelo Pure Logit supõe Independência de Alternativas Irrelevantes (IIA), o que significa que as elasticidades de preço cruzado são proporcionais às participações de mercado, o que pode ser irreal em muitos mercados. O BLP propõe heterogeneidade do consumidor ao permitir coeficientes aleatórios em preço e características, levando a padrões de substituição mais flexíveis.

5 5. Random Coefficient model

1. Suppose agents have the following utility function, where i denotes the agent, and j denotes the product:

$$u_{ij} = \underbrace{\delta_j}_{x'_j - \alpha p_j + \xi_j} + \sum_{k \in \{1,2\}} \sigma_k \nu_{ik} x_{jk} - \sigma_p \nu_{ip} p_j + \epsilon_{ij}$$

where ϵ_{ij} is an iid error following a standard Type-I Extreme Value distribution, and $\nu_{i \cdot} \stackrel{iid}{\sim} \mathcal{N}(0, 1)$ is an iid standard normal error. To summarize: the model is as before, but with random coefficients on the constant, the first characteristic, and price. The orthogonality/exogeneity assumptions remain the same as before.

- 1.a. What is the contraction mapping used here for the inner loop? Is there a way to reduce the computational burden from the contraction mapping? (Hint: take a look at page 4 of the appendix to Nevo (2000).) In the following, make sure to set the “inner tolerance” level for the contraction mapping very tight, in your final run ideally on the order of 10^{-14} .

Contraction mapping é usado para encontrar a utilidade média δ_j correspondente ao marketshare s_j previsto pelo modelo. O modelo assume que as utilidades dos produtos convergirá média, assim podemos prever a utilidade média de um produto no próximo período dentro de uma margem de erro (que nesse caso será de 10^{-14}). A fórmula é:

$$\delta_j^{t+1} = \delta_j^t + \ln(s_j^{obs}) - \ln(s_j(\delta^t, \theta))$$

```
[246]: X1_formulation = pyblp.Formulation('prices + char1 + char2 + char3 + costsh1 +_
      ↪costsh2', absorb='C(market_ids)')
X2_formulation = pyblp.Formulation('prices + char1 + char2 + char3 + costsh1 +_
      ↪costsh2')
product_formulations = (X1_formulation, X2_formulation)

mc_integration = pyblp.Integration('monte_carlo', size=247,_
      ↪specification_options={'seed': 0})
mc_problem = pyblp.Problem(product_formulations, data,_
      ↪integration=mc_integration)
bfgs = pyblp.Optimization('bfgs', {'gtol': 1e-14})

results1 = mc_problem.solve(sigma=np.ones((7, 7)), optimization=bfgs)
```

```

results1

#results2 = mc_problem.solve(sigma=np.eye(7), optimization=bfgs)
#results2

```

Initializing the problem ...
 Absorbing demand-side fixed effects ...
 Initialized the problem after 00:00:00.

Dimensions:

```

=====
  T   N   F   I   K1  K2  MD  ED
  --- --- --- --- --- --- ---
10  247  11  2470  6   7   5   1
=====

```

Formulations:

```

=====
=====
      Column Indices:      0      1      2      3      4      5
6
-----
-----
X1: Linear Characteristics  prices  char1  char2  char3  costsh1  costsh2
X2: Nonlinear Characteristics  1      prices  char1  char2  char3  costsh1
costsh2
=====
=====

```

Solving the problem ...

Nonlinear Coefficient Initial Values:

```

=====
=====
=====
=====
=====
Sigma:          1          prices          char1
char2          char3          costsh1          costsh2
| Sigma Squared:          1          prices          char1
char2          char3          costsh1          costsh2
-----
-----
-----
-----
-----
1      +1.00000000000000E+00
|      1      +1.00000000000000E+00  +1.00000000000000E+00
+1.00000000000000E+00  +1.00000000000000E+00  +1.00000000000000E+00

```

```

+1.000000000000000E+00 +1.000000000000000E+00
prices +1.000000000000000E+00 +1.000000000000000E+00
|      prices      +1.000000000000000E+00 +2.000000000000000E+00
+2.000000000000000E+00 +2.000000000000000E+00 +2.000000000000000E+00
+2.000000000000000E+00 +2.000000000000000E+00
char1 +1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
|      char1      +1.000000000000000E+00 +2.000000000000000E+00
+3.000000000000000E+00 +3.000000000000000E+00 +3.000000000000000E+00
+3.000000000000000E+00 +3.000000000000000E+00
char2 +1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
+1.000000000000000E+00
|      char2      +1.000000000000000E+00 +2.000000000000000E+00
+3.000000000000000E+00 +4.000000000000000E+00 +4.000000000000000E+00
+4.000000000000000E+00 +4.000000000000000E+00
char3 +1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
+1.000000000000000E+00 +1.000000000000000E+00
|      char3      +1.000000000000000E+00 +2.000000000000000E+00
+3.000000000000000E+00 +4.000000000000000E+00 +5.000000000000000E+00
+5.000000000000000E+00 +5.000000000000000E+00
costsh1 +1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
+1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
|      costsh1    +1.000000000000000E+00 +2.000000000000000E+00
+3.000000000000000E+00 +4.000000000000000E+00 +5.000000000000000E+00
+6.000000000000000E+00 +6.000000000000000E+00
costsh2 +1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
+1.000000000000000E+00 +1.000000000000000E+00 +1.000000000000000E+00
+1.000000000000000E+00 |      costsh2    +1.000000000000000E+00
+2.000000000000000E+00 +3.000000000000000E+00 +4.000000000000000E+00
+5.000000000000000E+00 +6.000000000000000E+00 +7.000000000000000E+00
=====
=====
=====
=====
=====
=====
=====

```

Starting optimization ...

The model may be under-identified. The total number of unfixed parameters is 34, which is more than the total number of moments, 5. Consider checking whether instruments were properly specified when initializing the problem, and whether parameters were properly configured when solving the problem.

GMM	Computation	Optimization	Objective	Fixed Point	Contraction	Clipped
Objective		Objective		Gradient		
Step	Time	Iterations	Evaluations	Iterations	Evaluations	Shares
Value		Improvement		Norm		
Theta						
----	-----	-----	-----	-----	-----	-----
-----	-----	-----	-----	-----	-----	-----

```

-----
-----
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```

```

1      00:00:00      0      1      289      875      0
+2.1095646627429E-26      +1.4360154494112E-12
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00
1      00:00:00      0      2      289      874      0
+2.0244918422545E-26 +8.5072820488317E-28 +1.5408216236289E-12
+9.9999999999994E-01, +1.0000000000000E+00, +1.0000000000002E+00,
+9.9999999999991E-01, +9.9999999999938E-01, +1.0000000000002E+00,
+1.00000000000014E+00, +1.00000000000012E+00, +1.0000000000001E+00,
+1.0000000000000E+00, +1.00000000000014E+00, +1.00000000000014E+00,
+1.00000000000003E+00, +1.0000000000000E+00, +9.999999999997E-01,
+9.9999999999985E-01, +9.9999999999988E-01, +1.0000000000001E+00,
+1.00000000000002E+00, +1.0000000000001E+00, +9.999999999996E-01,
+9.9999999999983E-01, +9.9999999999984E-01, +1.0000000000001E+00,
+1.0000000000001E+00, +1.0000000000001E+00, +9.999999999995E-01,
+9.999999999997E-01

```

```

ERROR:tornado.application:Exception in callback functools.partial(<bound method
OutputStream._flush of <ipykernel.iostream.OutputStream object at 0x7f1096bfb6a0>>)
Traceback (most recent call last):

```

```

  File "/home/hspassos/anaconda3/envs/blr_python/lib/python3.12/site-
packages/tornado/ioloop.py", line 750, in _run_callback

```

```

    ret = callback()
    ~~~~~

```

```

  File "/home/hspassos/anaconda3/envs/blr_python/lib/python3.12/site-
packages/ipykernel/iostream.py", line 639, in _flush

```

```

    msg = self.session.msg("stream", content, parent=parent)
    ~~~~~

```

```

  File "/home/hspassos/anaconda3/envs/blr_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 661, in msg

```

```

    header = self.msg_header(msg_type) if header is None else header
    ~~~~~

```

```

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 644, in msg_header
    return msg_header(self.msg_id, msg_type, self.username, self.session)
    ~~~~~

```

```

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 275, in msg_header
    date = utcnow()
    ~~~~~

```

```

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 203, in utcnow
    return datetime.utcnow().replace(tzinfo=utc)
    ~~~~~

```

DeprecationWarning: datetime.datetime.utcnow() is deprecated and scheduled for removal in a future version. Use timezone-aware objects to represent datetimes in UTC: datetime.datetime.now(datetime.UTC).

```

1      00:00:00      1      4      287      871      0
+2.9563479070908E-26      +1.8955266408674E-12
+9.9999999999999E-01, +1.0000000000000E+00, +1.0000000000000E+00,
+9.9999999999981E-01, +9.9999999999986E-01, +1.0000000000000E+00,
+1.00000000000003E+00, +1.00000000000003E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,
+1.00000000000001E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999997E-01, +9.9999999999997E-01, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999996E-01, +9.9999999999997E-01, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999999E-01

```

```

1      00:00:00      1      5      289      878      0
+1.9920805256139E-26      +1.5614458852229E-12
+9.9999999999999E-01, +1.0000000000000E+00, +1.0000000000000E+00,
+9.9999999999981E-01, +9.9999999999986E-01, +1.0000000000000E+00,
+1.00000000000003E+00, +1.00000000000003E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,
+1.00000000000001E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999997E-01, +9.9999999999997E-01, +1.0000000000000E+00,
+1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999996E-01, +9.9999999999997E-01, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999999E-01

```

```

1      00:00:00      1      6      287      871      0
+2.9563479070908E-26      +1.8955266408674E-12
+9.9999999999999E-01, +1.0000000000000E+00, +1.0000000000000E+00,
+9.9999999999981E-01, +9.9999999999986E-01, +1.0000000000000E+00,
+1.00000000000003E+00, +1.00000000000003E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,
+1.00000000000001E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+9.9999999999997E-01, +9.9999999999997E-01, +1.0000000000000E+00,

```

```

+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.99999999999996E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999999E-01
  1      00:00:00      1      7      289      878      0
+2.9329679174586E-26      +1.8833304272592E-12
+9.9999999999999E-01, +1.00000000000000E+00, +1.00000000000000E+00,
+9.99999999999981E-01, +9.99999999999986E-01, +1.00000000000000E+00,
+1.00000000000003E+00, +1.00000000000003E+00, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,
+1.00000000000001E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999997E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999996E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999999E-01
  1      00:00:01      1      8      286      868      0
+4.2320586612017E-26      +1.8842642122031E-12
+9.9999999999999E-01, +1.00000000000000E+00, +1.00000000000000E+00,
+9.99999999999981E-01, +9.99999999999986E-01, +1.00000000000000E+00,
+1.00000000000003E+00, +1.00000000000003E+00, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,
+1.00000000000001E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999997E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999996E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999999E-01
  1      00:00:00      1      9      289      878      0
+1.9920805256139E-26      +1.5614458852229E-12
+9.9999999999999E-01, +1.00000000000000E+00, +1.00000000000000E+00,
+9.99999999999981E-01, +9.99999999999986E-01, +1.00000000000000E+00,
+1.00000000000003E+00, +1.00000000000003E+00, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,
+1.00000000000001E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999997E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999996E-01, +9.9999999999997E-01, +1.00000000000000E+00,
+1.00000000000000E+00, +1.00000000000000E+00, +9.999999999999E-01,
+9.9999999999999E-01

```

The optimization routine failed to converge. This problem can sometimes be mitigated by choosing more reasonable initial parameter values, setting more conservative bounds, or configuring other optimization settings.

Optimization failed after 00:00:04.

Computing the Hessian and updating the weighting matrix ...

```

-----
KeyboardInterrupt                                Traceback (most recent call last)
Cell In[246], line 9
      6 mc_problem = pyblp.Problem(product_formulations, data,
    ↪ integration=mc_integration)
      7 bfgs = pyblp.Optimization('bfgs', {'gtol': 1e-14})
----> 9 results1 = mc_problem.solve(sigma=np.ones((7, 7)), optimization=bfgs)
     10 results1
     12 #results2 = mc_problem.solve(sigma=np.eye(7), optimization=bfgs)
     13 #results2

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/economies/
    ↪ problem.py:715, in ProblemEconomy.solve(self, sigma, pi, rho, beta, gamma,
    ↪ sigma_bounds, pi_bounds, rho_bounds, beta_bounds, gamma_bounds, delta, method,
    ↪ initial_update, optimization, scale_objective, check_optimality,
    ↪ finite_differences, error_behavior, error_punishment, delta_behavior,
    ↪ iteration, fp_type, shares_bounds, costs_bounds, W, center_moments, W_type,
    ↪ se_type, covariance_moments_mean, micro_moments, micro_sample_covariances,
    ↪ resample_agent_data)
       713 else:
       714     output("Estimating standard errors ...")
--> 715 final_progress = compute_step_progress(
       716     ↪ theta, progress, compute_gradient, compute_hessian, compute_micro_covariances,
       717     ↪ detect_micro_collinearity, compute_simulation_covariances
       718 )
       719 iteration_stats.append(final_progress.iteration_stats)
       720 optimization_stats.evaluations += 1

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/economies/
    ↪ problem.py:1172, in ProblemEconomy._compute_progress(self, parameters,
    ↪ moments, iv, W, scale_objective, error_behavior, error_punishment,
    ↪ delta_behavior, iteration, fp_type, shares_bounds, costs_bounds,
    ↪ finite_differences, covariance_moments_mean, resample_agent_data, theta,
    ↪ progress, compute_gradient, compute_hessian, compute_micro_covariances,
    ↪ detect_micro_collinearity, compute_simulation_covariances, agents_override)
     1169     return perturbed_progress.gradient
     1171     # compute the Hessian, enforcing shape and symmetry
-> 1172     hessian =
    ↪ compute_finite_differences(compute_perturbed_gradient, theta)
     1173     hessian = np.c_[hessian + hessian.T] / 2
     1175 # optionally resample agents to compute simulation covariances

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/utilities/
    ↪ basics.py:412, in compute_finite_differences(f, x, epsilon_scale)
     410     x1[index] += epsilon / 2
     411     x2[index] -= epsilon / 2
--> 412     arrays.append((f(x1) - f(x2)) / epsilon)
     414 if len(arrays[0].shape) == 1 or (len(arrays[0].shape) == 2 and arrays[0].
    ↪ shape[1] == 1):

```

```
415     return np.column_stack(arrays)
```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblr/economies/
 problem.py:1162, in ProblemEconomy._compute_progress.<locals>.

```
→ compute_perturbed_gradient(perturbed_theta)
1160 def compute_perturbed_gradient(perturbed_theta: Array) -> Array:
1161     """Evaluate the gradient at a perturbed parameter vector."""
-> 1162     perturbed_progress = self._compute_progress(
1163
→         parameters, moments, iv, W, scale_objective, error_behavior, error_punishment, delta_behavior,
1164
→         iteration, fp_type, shares_bounds, costs_bounds, finite_differences, covariance_moments_mean,
1165
→         resample_agent_data, perturbed_theta, progress, compute_gradient=True, compute_hessian=False,
1166         compute_micro_covariances=False, detect_micro_collinearity=False,
1167         compute_simulation_covariances=False,
1168     )
1169     return perturbed_progress.gradient
```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblr/economies/

```
→ problem.py:839, in ProblemEconomy._compute_progress(self, parameters, moments, iv, W, scale_objective, error_behavior, error_punishment, delta_behavior,
→ iteration, fp_type, shares_bounds, costs_bounds, finite_differences, covariance_moments_mean, resample_agent_data, theta, progress,
→ compute_gradient, compute_hessian, compute_micro_covariances, detect_micro_collinearity, compute_simulation_covariances, agents_override)
837 parts_collinearity_candidate_values: Dict[Hashable, Dict[MicroDataset, Array]] = {}
838 generator = generate_items(self.unique_market_ids, market_factory, ProblemMarket.solve)
-> 839 for t, generated_t in generator:
840     (
841
→         delta_t, xi_jacobian_t, parts_numerator_t, parts_denominator_t, parts_numerator_jacobian_t,
842
→         parts_denominator_jacobian_t, parts_covariances_numerator_t, weights_matching_t, value_matching_t,
843
→         clipped_shares_t, iteration_stats_t, tilde_costs_t, omega_jacobian_t, clipped_costs_t,
844     ) = generated_t
846     delta[self.product_market_indices[t]] = delta_t
```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblr/utilities/

```
→ basics.py:164, in <genexpr>(.0)
159 """Generate (key, method(*factory(key))) tuples for each key. The first
→ element returned by factory is an instance
160 of the class to which method is attached. If a process pool has been
→ initialized, use multiprocessing; otherwise,
161 use serial processing.
162 """
```



```

163 if pool is None:
--> 164     return (generate_items_worker((k, factory(k), method)) for k in key.)
165 return pool.imap_unordered(generate_items_worker, ((k, factory(k),
↳method) for k in keys))

```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/utilities/
↳basics.py:173, in generate_items_worker(args)

```

169 """Call the specified method of a class instance with any additional
↳arguments. Return the associated key along with
170 the returned object.
171 """
172 key, (instance, *method_args), method = args
--> 173 return key, method(instance, *method_args)

```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/utilities/
↳basics.py:665, in NumericalErrorHandler.__call__.<locals>.wrapper(*args,
↳**kwargs)

```

663 with np.errstate(divide='call', over='call', under='ignore',
↳invalid='call'):
664     np.seterrcall(detector)
--> 665     returned = decorated(*args, **kwargs)
666 if detector.detected is not None:
667     returned[-1].append(detector.detected)

```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/markets/
↳problem_market.py:37, in ProblemMarket.solve(self, delta, last_delta,
↳last_tilde_costs, moments, iteration, fp_type, shares_bounds, costs_bounds,
↳compute_jacobians, compute_micro_covariances, keep_micro_mappings)

```

34 errors: List[Error] = []
36 # solve the contraction
---> 37 delta, clipped_shares, stats, delta_errors =
↳self.safely_compute_delta(delta, iteration, fp_type, shares_bounds)
38 errors.extend(delta_errors)
40 # replace invalid values in delta with their last computed values

```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/utilities/
↳basics.py:665, in NumericalErrorHandler.__call__.<locals>.wrapper(*args,
↳**kwargs)

```

663 with np.errstate(divide='call', over='call', under='ignore',
↳invalid='call'):
664     np.seterrcall(detector)
--> 665     returned = decorated(*args, **kwargs)
666 if detector.detected is not None:
667     returned[-1].append(detector.detected)

```

File ~/anaconda3/envs/blr_python/lib/python3.12/site-packages/pyblp/markets/
↳problem_market.py:145, in ProblemMarket.safely_compute_delta(self,
↳initial_delta, iteration, fp_type, shares_bounds)

```

138 @NumericalErrorHandler(exceptions.DeltaNumericalError)

```

```

139 def safely_compute_delta(
140     self, initial_delta: Array, iteration: Iteration, fp_type: str,
↪ shares_bounds: Bounds) -> (
141     Tuple[Array, Array, SolverStats, List[Error]]):
142     """Compute the mean utility for this market that equates market_
↪ shares to observed values by solving a fixed
143     point problem, handling any numerical errors.
144     """
--> 145     delta, clipped_shares, stats, errors =
↪ self.compute_delta(initial_delta, iteration, fp_type, shares_bounds)
146     if not stats.converged:
147         errors.append(exceptions.DeltaConvergenceError())

```

File ~/anaconda3/envs/blp_python/lib/python3.12/site-packages/pyblp/markets/
↪ market.py:568, in Market.compute_delta(self, initial_delta, iteration,
↪ fp_type, shares_bounds)

```

565         return x, None, jacobian
566     # solve the linear fixed point problem
--> 568     delta, stats = iteration._iterate(initial_delta, contraction)
569 else:
570     # solve for delta with a nonlinear fixed point
571     assert 'nonlinear' in fp_type and self.epsilon_scale == 1

```

File ~/anaconda3/envs/blp_python/lib/python3.12/site-packages/pyblp/
↪ configurations/iteration.py:284, in Iteration._iterate(self, initial,
↪ contraction)

```

281 raw_initial = initial.astype(np.float64, copy=False).flatten()
282 # solve the problem and convert the raw final values to the same data_
↪ type and shape as the initial values
--> 284 raw_final, converged = self._iterator(
285     raw_initial, contraction_wrapper, iteration_callback, **self._method_options
286 )
287 final = np.asarray(raw_final).astype(initial.dtype, copy=False).
↪ reshape(initial.shape)
288 stats = SolverStats(converged, iterations, evaluations)

```

File ~/anaconda3/envs/blp_python/lib/python3.12/site-packages/pyblp/
↪ configurations/iteration.py:442, in squarem_iterator(initial, contraction,
↪ iteration_callback, max_evaluations, atol, rtol, norm, scheme, step_min,
↪ step_max, step_factor)

```

440 # acceleration step
441 x2, x = x, x0 - 2 * alpha * r + alpha**2 * v
--> 442 x3, (x, weights) = x, contraction(x)[:2]
443 if not all_finite(x, weights):
444     x = x2

```

```

File ~/anaconda3/envs/blp_python/lib/python3.12/site-packages/pyblp/
↳ configurations/iteration.py:273, in Iteration._iterate.<locals>.
↳ contraction_wrapper(raw_values)
    271     raw_values = np.asarray(raw_values)
    272     values = raw_values.reshape(initial.shape).astype(initial.dtype,
↳ copy=False)
--> 273     values, weights, jacobian = contraction(values, iterations, evaluations
    274     return (
    275         values.astype(raw_values.dtype, copy=False).reshape(raw_values.
↳ shape),
    276         None if weights is None else weights.astype(raw_values.dtype,
↳ copy=False).reshape(raw_values.shape),
    277         None if jacobian is None else jacobian.astype(raw_values.dtype,
↳ copy=False)
    278 )

File ~/anaconda3/envs/blp_python/lib/python3.12/site-packages/pyblp/markets/
↳ market.py:540, in Market.compute_delta.<locals>.contraction(x, iterations,
↳ evaluations)
    538     probabilities = compute_probabilities(x)[0]
    539     shares = probabilities @ self.agents.weights
--> 540     clip_shares(shares)
    541     x0, x = x, x + log_shares - np.log(shares)
    542     universal_display(x0, x, iterations, evaluations)

File ~/anaconda3/envs/blp_python/lib/python3.12/site-packages/pyblp/markets/
↳ market.py:521, in Market.compute_delta.<locals>.clip_shares(shares)
    518         clipped_shares = small_shares | large_shares
    520     elif np.isfinite(shares_bounds[0]):
--> 521         def clip_shares(shares: Array) -> None:
    522             """Clip shares from below."""
    523             nonlocal clipped_shares

KeyboardInterrupt:

```

```
[161]: results2 = mc_problem.solve(sigma=np.eye(7), optimization=bfgs)
results2
```

Solving the problem ...

Nonlinear Coefficient Initial Values:

```

=====
=====
=
Sigma:          1          prices          char1
char2          char3          costsh1          costsh2
-----
-----

```

```

-----
1      +1.0000000000000E+00
prices +0.0000000000000E+00 +1.0000000000000E+00
char1  +0.0000000000000E+00 +0.0000000000000E+00 +1.0000000000000E+00
char2  +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+1.0000000000000E+00
char3  +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+0.0000000000000E+00 +1.0000000000000E+00
costsh1 +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+0.0000000000000E+00 +0.0000000000000E+00 +1.0000000000000E+00
costsh2 +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+1.0000000000000E+00
=====
=====
=

```

Nonlinear Coefficient Lower Bounds:

```

=====
=====
=
Sigma:          1          prices          char1
char2          char3          costsh1          costsh2
-----
-----
-----
1          -INF
prices +0.0000000000000E+00          -INF
char1  +0.0000000000000E+00 +0.0000000000000E+00          -INF
char2  +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
-INF
char3  +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+0.0000000000000E+00          -INF
costsh1 +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+0.0000000000000E+00 +0.0000000000000E+00          -INF
costsh2 +0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00
+0.0000000000000E+00 +0.0000000000000E+00 +0.0000000000000E+00          -INF
=====
=====
=

```

Nonlinear Coefficient Upper Bounds:

```

=====
=====
=
Sigma:          1          prices          char1
char2          char3          costsh1          costsh2
-----
-----

```

```

-----
-----
1          +INF
prices    +0.000000000000E+00          +INF
char1     +0.000000000000E+00 +0.000000000000E+00          +INF
char2     +0.000000000000E+00 +0.000000000000E+00 +0.000000000000E+00
+INF
char3     +0.000000000000E+00 +0.000000000000E+00 +0.000000000000E+00
+0.000000000000E+00          +INF
costsh1   +0.000000000000E+00 +0.000000000000E+00 +0.000000000000E+00
+0.000000000000E+00 +0.000000000000E+00          +INF
costsh2   +0.000000000000E+00 +0.000000000000E+00 +0.000000000000E+00
+0.000000000000E+00 +0.000000000000E+00 +0.000000000000E+00          +INF
=====
=====
=

```

Starting optimization ...

The model may be under-identified. The total number of unfixed parameters is 13, which is more than the total number of moments, 5. Consider checking whether instruments were properly specified when initializing the problem, and whether parameters were properly configured when solving the problem.

GMM Objective	Computation Time	Optimization Objective Iterations Improvement	Objective Evaluations	Fixed Point Gradient Iterations Norm	Contraction Evaluations	Clipped Shares
1	00:00:00	0	1	152	466	0
+8.9635197677287E-27				+3.7197706976986E-13		
+1.000000000000E+00,		+1.000000000000E+00,		+1.000000000000E+00,		
+1.000000000000E+00,		+1.000000000000E+00,		+1.000000000000E+00,		
+1.000000000000E+00						
1	00:00:00	0	2	153	466	0
+1.1365907480957E-26				+2.4272527585076E-13		
+9.9999999999999E-01,		+9.9999999999963E-01,		+9.9999999999973E-01,		
+1.0000000000002E+00,		+1.0000000000000E+00,		+9.999999999999E-01,		
+9.999999999999E-01						
1	00:00:00	0	3	151	464	0
+1.0669137757789E-26				+3.0739409171452E-13		
+1.0000000000000E+00,		+9.9999999999991E-01,		+9.9999999999994E-01,		
+1.0000000000001E+00,		+1.0000000000000E+00,		+1.0000000000000E+00,		
+1.0000000000000E+00						

1	00:00:00	0	4	152	465	0
+1.2301786229545E-26 +3.1210840751105E-13						
+1.0000000000000E+00, +9.9999999999998E-01, +9.9999999999999E-01,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	5	151	463	0
+1.0095763037280E-26 +3.4684848159347E-13						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	6	152	465	0
+9.3494129523740E-27 +2.1150956344006E-13						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	7	153	466	0
+1.1917740463648E-26 +5.5019121699312E-13						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	8	152	466	0
+8.9635197677287E-27 +3.7197706976986E-13						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	9	153	466	0
+1.1365907480957E-26 +2.4272527585076E-13						
+9.9999999999999E-01, +9.9999999999963E-01, +9.9999999999973E-01,						
+1.0000000000002E+00, +1.0000000000000E+00, +9.9999999999999E-01,						
+9.9999999999999E-01						
1	00:00:00	0	10	151	465	0
+1.3217532034510E-26 +5.0285435273880E-13						
+9.9999999999999E-01, +9.9999999999982E-01, +9.9999999999987E-01,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.9999999999999E-01,						
+1.0000000000000E+00						
1	00:00:00	0	11	151	464	0
+1.3637691107537E-26 +3.6957567372597E-13						
+1.0000000000000E+00, +9.9999999999993E-01, +9.9999999999995E-01,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	12	151	462	0
+1.0648897140064E-26 +4.2098003357311E-13						
+1.0000000000000E+00, +9.9999999999997E-01, +9.9999999999998E-01,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
1	00:00:00	0	13	152	466	0
+9.5215733570783E-27 +2.2724792234986E-13						
+1.0000000000000E+00, +9.9999999999999E-01, +9.9999999999999E-01,						

+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	0	14	152	464	0
+1.2693895229871E-26			+3.6955743320319E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	0	15	153	466	0
+7.7899683121292E-27 +1.1735514555995E-27 +1.9191466875898E-13						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	16	152	465	0
+1.0139815249664E-26			+4.4672412659205E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	17	152	465	0
+8.1821715010909E-27			+1.6223262548003E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	18	153	466	0
+7.7899683121292E-27			+1.9191466875898E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	19	152	465	0
+1.0139815249664E-26			+4.4672412659205E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	20	151	464	0
+9.7272583619471E-27			+2.3974216159463E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	21	153	466	0
+1.0711903189629E-26			+3.1753179573566E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						
1	00:00:00	1	22	153	466	0
+7.7899683121292E-27			+1.9191466875898E-13			
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+1.00000000000000E+00						

The optimization routine failed to converge. This problem can sometimes be mitigated by choosing more reasonable initial parameter values, setting more conservative bounds, or configuring other optimization settings.

Optimization failed after 00:00:03.

Computing the Hessian and and updating the weighting matrix ...

Computed results after 00:00:02.

Problem Results Summary:

```
=====
=====
GMM      Objective      Gradient      Hessian
Hessian  Clipped      Weighting Matrix
Step      Value      Norm      Min Eigenvalue      Max
Eigenvalue  Shares      Condition Number
-----
-----
1      +7.7899683121292E-27  +1.9191466875898E-13  -2.1941880127562E-05
+4.1381323863492E-05      0      +9.1579102736529E+01
=====
=====
```

Starting optimization ...

```
GMM  Computation  Optimization  Objective  Fixed Point  Contraction  Clipped
Objective      Objective
Step      Time      Iterations  Evaluations  Iterations  Evaluations  Shares
Value
Theta
-----
-----
2      00:00:00      0      1      0      10      0
+8.3314662674042E-27      +3.5399277824058E-13
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00
2      00:00:00      0      2      19      72      0
+9.5832410829883E-27      +6.0471461108433E-13
+9.9999999999999E-01, +1.0000000000000E+00, +9.9999999999999E-01,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+9.9999999999999E-01
2      00:00:00      0      3      11      39      0
+8.4415243908054E-27      +8.3545398289872E-13
+1.0000000000000E+00, +1.0000000000000E+00, +9.9999999999999E-01,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
```



```

+1.0000000000000000E+00
 2      00:00:00      0      4      1      21      0
+6.3573671462273E-27 +1.9740991211769E-27 +7.5026601248160E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0      5      4      24      0
+8.3711178230008E-27 +7.9593741277169E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0      6      1      21      0
+5.7616852070022E-27 +5.9568193922502E-28 +5.3175733267908E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0      7      3      23      0
+9.1658114707901E-27 +9.6343570743282E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0      8      1      21      0
+5.9363418430965E-27 +5.6271220450056E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0      9      1      21      0
+7.8824940785541E-27 +6.1865822222269E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0     10      1      21      0
+5.7616852070022E-27 +5.3175733267908E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00
 2      00:00:00      0     11      1      21      0
+7.8824940785541E-27 +6.1865822222269E-13
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00, +1.0000000000000000E+00, +1.0000000000000000E+00,
+1.0000000000000000E+00

```

```

ERROR:tornado.application:Exception in callback functools.partial(<bound method
OutStream._flush of <ipykernel.iostream.OutStream object at 0x7f1096bfb6a0>>)

```

```

Traceback (most recent call last):

```

```

  File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/tornado/ioloop.py", line 750, in _run_callback

```

```

    ret = callback()

```

```

~~~~~
File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/ipykernel/iostream.py", line 639, in _flush
    msg = self.session.msg("stream", content, parent=parent)
~~~~~

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 661, in msg
    header = self.msg_header(msg_type) if header is None else header
~~~~~

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 644, in msg_header
    return msg_header(self.msg_id, msg_type, self.username, self.session)
~~~~~

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 275, in msg_header
    date = utcnow()
~~~~~

File "/home/hspassos/anaconda3/envs/blp_python/lib/python3.12/site-
packages/jupyter_client/session.py", line 203, in utcnow
    return datetime.utcnow().replace(tzinfo=utc)
~~~~~

DeprecationWarning: datetime.datetime.utcnow() is deprecated and scheduled for
removal in a future version. Use timezone-aware objects to represent datetimes
in UTC: datetime.datetime.now(datetime.UTC).

  2      00:00:00      0      18      1      21      0
+5.7616852070022E-27      +5.3175733267908E-13
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00
  2      00:00:00      0      19      1      21      0
+7.8824940785541E-27      +6.1865822222269E-13
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00
  2      00:00:00      0      20      1      21      0
+5.7616852070022E-27      +5.3175733267908E-13
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+1.0000000000000E+00
  2      00:00:00      0      21      19      72      0
+9.5832410829883E-27      +6.0471461108433E-13
+9.9999999999999E-01, +1.0000000000000E+00, +9.9999999999999E-01,
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,
+9.9999999999999E-01
  2      00:00:00      0      22      16      61      0
+8.1764652982900E-27      +6.5929271794309E-13
+9.9999999999999E-01, +1.0000000000000E+00, +9.9999999999999E-01,

```

+1.00000000000001E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
2	00:00:00	0	23	18	68	0
+6.5351327668380E-27			+7.6696411209601E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000002E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+1.0000000000000E+00						
2	00:00:00	0	24	19	71	0
+7.5589633217122E-27			+5.3478663666325E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000003E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	25	19	70	0
+6.0631523025041E-27			+6.5926697498519E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000002E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	26	19	71	0
+1.0030544328411E-26			+6.9555238244526E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000003E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	27	19	72	0
+4.8864026296984E-27			+8.7528257730382E-28 +6.2486433780701E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000002E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	28	19	72	0
+8.8479763140511E-27			+8.6748439712425E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000003E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	29	19	71	0
+1.1588915424696E-26			+8.6759650561113E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000002E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	30	20	73	0
+6.0967049088638E-27			+6.1533619431677E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000002E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						
2	00:00:00	0	31	18	69	0
+6.5375299705659E-27			+6.6649400204766E-13			
+9.9999999999999E-01, +1.00000000000003E+00, +9.9999999999997E-01,						
+1.00000000000002E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999999E-01						

The optimization routine failed to converge. This problem can sometimes be mitigated by choosing more reasonable initial parameter values, setting more conservative bounds, or configuring other optimization settings.

Optimization failed after 00:00:01.

Computing the Hessian and estimating standard errors ...

Computed results after 00:00:01.

Problem Results Summary:

=====						
=====						
GMM	Objective	Gradient		Hessian		
Hessian	Clipped	Weighting Matrix		Covariance Matrix		
Step	Value	Norm		Min Eigenvalue		Max
Eigenvalue	Shares	Condition	Number	Condition Number		

2	+8.3314662674042E-27	+3.5399277824058E-13	-2.3998431332276E-05			
+2.8380720415443E-05	0	+1.8856983557030E+02	+4.9371086509037E+18			
=====						
=====						

Cumulative Statistics:

=====					
Computation	Optimizer	Optimization	Objective	Fixed Point	Contraction
Time	Converged	Iterations	Evaluations	Iterations	Evaluations

00:00:07	No	1	55	3755	11960
=====					

Nonlinear Coefficient Estimates (Robust SEs in Parentheses):

=====					
=====					
=====					
Sigma:	1	prices		char1	
char2		char3	costsh1		costsh2

1	+1.0000000000000E+00 (+6.9622432663470E-03)				
prices	+0.0000000000000E+00		+1.0000000000000E+00 (+1.1737609212766E-01)		
char1	+0.0000000000000E+00		+0.0000000000000E+00		+1.0000000000000E+00 (+9.0953194355645E-02)

```

char2    +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+1.000000000000E+00
(+1.0909120619031E-01)

```

```

char3    +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+0.000000000000E+00    +1.000000000000E+00
(+1.8631450401344E-01)

```

```

costsh1  +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+0.000000000000E+00    +0.000000000000E+00    +1.000000000000E+00
(+1.5108293984020E-02)

```

```

costsh2  +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+1.000000000000E+00
(+1.8371386259109E-02)

```

```

=====
=====
=====

```

Beta Estimates (Robust SEs in Parentheses):

```

=====
=====
prices          char1          char2
char3          costsh1        costsh2
-----
-2.2313863244623E+00    -1.9431473549215E-02    -5.0087268870514E-02
+4.6325483590655E-01    -1.5282164349516E+00    -1.2621283788897E+00
(+8.4358996302135E-02)  (+1.4630974707531E-01)  (+1.8136509195552E-01)
(+1.3736290110478E-01)  (+2.7318420317347E-01)  (+3.1591550864354E-01)
=====
=====

```

[161]: Problem Results Summary:

```

=====
=====
GMM          Objective          Gradient          Hessian
Hessian      Clipped          Weighting Matrix  Covariance Matrix
Step         Value              Norm              Min Eigenvalue    Max
Eigenvalue   Shares            Condition Number  Condition Number
-----
2            +8.3314662674042E-27    +3.5399277824058E-13    -2.3998431332276E-05
+2.8380720415443E-05    0            +1.8856983557030E+02    +4.9371086509037E+18
=====

```

=====
Cumulative Statistics:

```
=====
Computation  Optimizer  Optimization  Objective  Fixed Point  Contraction
  Time      Converged  Iterations   Evaluations  Iterations   Evaluations
-----
00:00:07      No          1           55          3755         11960
=====
```

Nonlinear Coefficient Estimates (Robust SEs in Parentheses):

```
=====
=====
=====
Sigma:          1          prices          char1
char2          char3          costsh1          costsh2
-----
-----
-----
1      +1.000000000000E+00
      (+6.9622432663470E-03)

prices    +0.000000000000E+00    +1.000000000000E+00
      (+1.1737609212766E-01)

char1     +0.000000000000E+00    +0.000000000000E+00    +1.000000000000E+00
      (+9.0953194355645E-02)

char2     +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+1.000000000000E+00
      (+1.0909120619031E-01)

char3     +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+0.000000000000E+00    +1.000000000000E+00
      (+1.8631450401344E-01)

costsh1   +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+0.000000000000E+00    +0.000000000000E+00    +1.000000000000E+00
      (+1.5108293984020E-02)

costsh2   +0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+0.000000000000E+00    +0.000000000000E+00    +0.000000000000E+00
+1.000000000000E+00
      (+1.8371386259109E-02)
=====
=====
=====
```

Beta Estimates (Robust SEs in Parentheses):

prices			char1		char2	
char3		costsh1		costsh2		
-2.2313863244623E+00		-1.9431473549215E-02		-5.0087268870514E-02		
+4.6325483590655E-01		-1.5282164349516E+00		-1.2621283788897E+00		
(+8.4358996302135E-02)		(+1.4630974707531E-01)		(+1.8136509195552E-01)		
(+1.3736290110478E-01)		(+2.7318420317347E-01)		(+3.1591550864354E-01)		

1.b. Write the parameter vector of interest as $\theta = (\theta_1, \theta_2)$, where θ_1 are the “linear” parameters, and “_2” are the “nonlinear” parameters. Which parameters are in θ_1 and which are in θ_2 ? What does this imply for estimation?

```
[137]: theta_1 = pd.DataFrame(logit_results.beta)
theta_2 = pd.DataFrame(results2.beta)
theta_1
theta_2
```

```
[137]:      0
0    4.018726
1   -1.874091
2   -0.368675
3   -0.303791
4    0.452330
5   -1.865919
6   -1.473477
7   -0.789412
8    0.215525
9   -0.795686
10  -0.517398
11  -0.863983
12   0.769933
13  -0.301054
14  -2.337703
15  -1.704664
```

1.c. Bonus question: Explain how the variance terms σ are identified from variation in the choice set and prices.

1.d. Estimate the model using 2-step optimal GMM. In addition to your point estimates, please provide standard errors (Hint: take a look at page 6 of the appendix to Nevo (2000) for analytic standard errors, and/or use finite differences for a numerical approximation). If you try different starting values, do your estimates change?

```
[165]: results3 = mc_problem.solve(sigma=np.ones((7, 7)), method='2s',
    ↪optimization=bfgs)
results3

print("Parameter Estimates:")
print(results3.beta)
print(results3.sigma)
```

Solving the problem ...

Nonlinear Coefficient Initial Values:

```
=====
=====
=====
=====
=====
=====
Sigma:          1          prices          char1
char2          char3          costsh1          costsh2
| Sigma Squared:          1          prices          char1
char2          char3          costsh1          costsh2
-----
-----
-----
-----
-----
-----
1          +1.0000000000000E+00
|          1          +1.0000000000000E+00 +1.0000000000000E+00
+1.0000000000000E+00 +1.0000000000000E+00 +1.0000000000000E+00
+1.0000000000000E+00 +1.0000000000000E+00
prices +1.0000000000000E+00 +1.0000000000000E+00
| prices +1.0000000000000E+00 +2.0000000000000E+00
+2.0000000000000E+00 +2.0000000000000E+00 +2.0000000000000E+00
+2.0000000000000E+00 +2.0000000000000E+00
char1 +1.0000000000000E+00 +1.0000000000000E+00 +1.0000000000000E+00
| char1 +1.0000000000000E+00 +2.0000000000000E+00
+3.0000000000000E+00 +3.0000000000000E+00 +3.0000000000000E+00
+3.0000000000000E+00 +3.0000000000000E+00
char2 +1.0000000000000E+00 +1.0000000000000E+00 +1.0000000000000E+00
+1.0000000000000E+00
| char2 +1.0000000000000E+00 +2.0000000000000E+00
+3.0000000000000E+00 +4.0000000000000E+00 +4.0000000000000E+00
+4.0000000000000E+00 +4.0000000000000E+00
char3 +1.0000000000000E+00 +1.0000000000000E+00 +1.0000000000000E+00
+1.0000000000000E+00 +1.0000000000000E+00
| char3 +1.0000000000000E+00 +2.0000000000000E+00
+3.0000000000000E+00 +4.0000000000000E+00 +5.0000000000000E+00
+5.0000000000000E+00 +5.0000000000000E+00
costsh1 +1.0000000000000E+00 +1.0000000000000E+00 +1.0000000000000E+00
```


1	00:00:00	0	2	289	874	0
+2.0244918422545E-26 +8.5072820488317E-28 +1.5408216236289E-12						
+9.9999999999994E-01, +1.0000000000000E+00, +1.0000000000002E+00,						
+9.9999999999911E-01, +9.9999999999938E-01, +1.0000000000002E+00,						
+1.00000000000014E+00, +1.00000000000012E+00, +1.0000000000001E+00,						
+1.0000000000000E+00, +1.00000000000014E+00, +1.00000000000014E+00,						
+1.00000000000003E+00, +1.0000000000000E+00, +9.999999999997E-01,						
+9.9999999999985E-01, +9.9999999999988E-01, +1.0000000000001E+00,						
+1.00000000000002E+00, +1.0000000000001E+00, +9.999999999996E-01,						
+9.9999999999983E-01, +9.9999999999984E-01, +1.0000000000001E+00,						
+1.0000000000001E+00, +1.0000000000001E+00, +9.999999999995E-01,						
+9.999999999997E-01						
1	00:00:00	0	3	289	878	0
+1.9920805256139E-26 +3.2411316640615E-28 +1.5614458852229E-12						
+9.999999999999E-01, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999981E-01, +9.9999999999986E-01, +1.0000000000000E+00,						
+1.00000000000003E+00, +1.00000000000003E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999997E-01, +9.999999999997E-01, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999996E-01, +9.999999999997E-01, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999999E-01						
1	00:00:00	1	4	287	871	0
+2.9563479070908E-26 +1.8955266408674E-12						
+9.999999999999E-01, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999981E-01, +9.9999999999986E-01, +1.0000000000000E+00,						
+1.00000000000003E+00, +1.00000000000003E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999997E-01, +9.999999999997E-01, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999996E-01, +9.999999999997E-01, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999999E-01						
1	00:00:00	1	5	289	878	0
+1.9920805256139E-26 +1.5614458852229E-12						
+9.999999999999E-01, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.9999999999981E-01, +9.9999999999986E-01, +1.0000000000000E+00,						
+1.00000000000003E+00, +1.00000000000003E+00, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.00000000000003E+00, +1.00000000000003E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999997E-01, +9.999999999997E-01, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999996E-01, +9.999999999997E-01, +1.0000000000000E+00,						
+1.0000000000000E+00, +1.0000000000000E+00, +9.999999999999E-01,						
+9.999999999999E-01						

1	00:00:00	1	6	287	871	0
+2.9563479070908E-26						+1.8955266408674E-12
+9.9999999999999E-01,						+1.0000000000000E+00,
+9.9999999999981E-01,						+9.9999999999986E-01,
+1.00000000000003E+00,						+1.0000000000000E+00,
+1.0000000000000E+00,						+1.00000000000003E+00,
+1.00000000000001E+00,						+1.0000000000000E+00,
+9.9999999999997E-01,						+9.9999999999999E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999996E-01,						+9.9999999999997E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999999E-01						
1	00:00:00	1	7	289	878	0
+2.9329679174586E-26						+1.8833304272592E-12
+9.9999999999999E-01,						+1.0000000000000E+00,
+9.9999999999981E-01,						+9.9999999999986E-01,
+1.00000000000003E+00,						+1.0000000000000E+00,
+1.0000000000000E+00,						+1.00000000000003E+00,
+1.00000000000001E+00,						+1.0000000000000E+00,
+9.9999999999997E-01,						+9.9999999999999E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999996E-01,						+9.9999999999997E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999999E-01						
1	00:00:00	1	8	286	868	0
+4.2320586612017E-26						+1.8842642122031E-12
+9.9999999999999E-01,						+1.0000000000000E+00,
+9.9999999999981E-01,						+9.9999999999986E-01,
+1.00000000000003E+00,						+1.0000000000000E+00,
+1.0000000000000E+00,						+1.00000000000003E+00,
+1.00000000000001E+00,						+1.0000000000000E+00,
+9.9999999999997E-01,						+9.9999999999999E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999996E-01,						+9.9999999999997E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999999E-01						
1	00:00:00	1	9	289	878	0
+1.9920805256139E-26						+1.5614458852229E-12
+9.9999999999999E-01,						+1.0000000000000E+00,
+9.9999999999981E-01,						+9.9999999999986E-01,
+1.00000000000003E+00,						+1.0000000000000E+00,
+1.0000000000000E+00,						+1.00000000000003E+00,
+1.00000000000001E+00,						+1.0000000000000E+00,
+9.9999999999997E-01,						+9.9999999999999E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999996E-01,						+9.9999999999997E-01,
+1.0000000000000E+00,						+1.0000000000000E+00,
+9.9999999999999E-01						

The optimization routine failed to converge. This problem can sometimes be mitigated by choosing more reasonable initial parameter values, setting more conservative bounds, or configuring other optimization settings.

Optimization failed after 00:00:02.

Computing the Hessian and and updating the weighting matrix ...

Computed results after 00:00:16.

Problem Results Summary:

=====					
=====					
GMM	Objective	Gradient	Hessian		
Hessian	Clipped	Weighting Matrix			
Step	Value	Norm	Min Eigenvalue	Max	
Eigenvalue	Shares	Condition Number			

1	+1.9920805256139E-26	+1.5614458852229E-12	-2.9176296080531E-04		
+3.1418709849730E-04	0	+9.1579102736529E+01			
=====					
=====					

Starting optimization ...

GMM	Computation	Optimization	Objective	Fixed Point	Contraction	Clipped						
Objective		Objective		Gradient								
Step	Time	Iterations	Evaluations	Iterations	Evaluations	Shares						
Value		Improvement		Norm								
Theta												

2	00:00:00	0	1	0	11	0						
+6.0533391004769E-26				+4.7124267143486E-13								
+9.9999999999999E-01,		+1.0000000000000E+00,		+1.0000000000000E+00,								
+9.9999999999981E-01,		+9.9999999999986E-01,		+1.0000000000000E+00,								
+1.0000000000003E+00,		+1.0000000000003E+00,		+1.0000000000000E+00,								
+1.0000000000000E+00,		+1.0000000000003E+00,		+1.0000000000003E+00,								
+1.0000000000001E+00,		+1.0000000000000E+00,		+9.9999999999999E-01,								

+9.999999999997E-01, +9.999999999997E-01, +1.000000000000E+00,						
+1.000000000000E+00, +1.000000000000E+00, +9.999999999999E-01,						
+9.999999999996E-01, +9.999999999997E-01, +1.000000000000E+00,						
+1.000000000000E+00, +1.000000000000E+00, +9.999999999999E-01,						
+9.999999999999E-01						
2	00:00:00	0	2	38	126	0
+3.1247090742030E-26 +2.9286300262740E-26 +4.1981634940432E-13						
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.0000000000001E+00,						
+1.0000000000001E+00, +9.999999999995E-01, +9.999999999998E-01,						
+9.9999999999965E-01, +1.0000000000005E+00, +1.0000000000005E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.999999999990E-01,						
+1.0000000000001E+00, +1.0000000000001E+00, +9.999999999997E-01,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.999999999995E-01, +9.999999999995E-01, +1.0000000000001E+00,						
+1.0000000000000E+00, +1.0000000000001E+00, +1.0000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	3	38	127	0
+5.0124789450571E-26 +4.9930396810756E-13						
+9.999999999998E-01, +9.9999999999960E-01, +9.9999999999953E-01,						
+9.9999999999946E-01, +9.9999999999965E-01, +1.0000000000001E+00,						
+1.0000000000001E+00, +9.999999999994E-01, +9.999999999998E-01,						
+9.9999999999962E-01, +1.0000000000005E+00, +1.0000000000006E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.9999999999989E-01,						
+1.0000000000001E+00, +1.0000000000001E+00, +9.999999999997E-01,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.999999999994E-01, +9.999999999995E-01, +1.0000000000001E+00,						
+1.0000000000000E+00, +1.0000000000001E+00, +1.0000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	4	37	122	0
+5.5345870726670E-26 +6.2549288652871E-13						
+9.999999999998E-01, +9.9999999999962E-01, +9.9999999999956E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.0000000000001E+00,						
+1.0000000000001E+00, +9.999999999995E-01, +9.999999999998E-01,						
+9.9999999999964E-01, +1.0000000000005E+00, +1.0000000000005E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.999999999990E-01,						
+1.0000000000001E+00, +1.0000000000001E+00, +9.999999999997E-01,						
+1.0000000000000E+00, +1.0000000000000E+00, +1.0000000000000E+00,						
+9.999999999995E-01, +9.999999999995E-01, +1.0000000000001E+00,						
+1.0000000000000E+00, +1.0000000000001E+00, +1.0000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	5	35	118	0
+4.6923353827549E-26 +4.0255780203410E-13						
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.0000000000001E+00,						
+1.0000000000001E+00, +9.999999999995E-01, +9.999999999998E-01,						
+9.9999999999965E-01, +1.0000000000005E+00, +1.0000000000005E+00,						
+1.0000000000001E+00, +1.0000000000000E+00, +9.999999999990E-01,						

+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	6	38	126	0
+3.1247090742030E-26				+4.1981634940432E-13		
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	7	38	127	0
+5.0124789450571E-26				+4.9930396810756E-13		
+9.999999999998E-01, +9.9999999999960E-01, +9.9999999999953E-01,						
+9.9999999999946E-01, +9.9999999999965E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999994E-01, +9.9999999999998E-01,						
+9.9999999999962E-01, +1.00000000000005E+00, +1.00000000000006E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999989E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.999999999994E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	8	37	123	0
+3.4308826922419E-26				+3.2724554800249E-13		
+9.999999999998E-01, +9.9999999999962E-01, +9.9999999999956E-01,						
+9.9999999999948E-01, +9.9999999999966E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999964E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	9	35	119	0
+6.6824555505262E-26				+4.7097457160500E-13		
+9.999999999998E-01, +9.9999999999962E-01, +9.9999999999956E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999964E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						

+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	10	35	118	0
+6.0963114828689E-26				+4.3727056907543E-13		
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999964E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	11	36	120	0
+5.3255367199067E-26				+4.7140564707289E-13		
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	12	37	124	0
+2.9012006319926E-26				+2.2350844221041E-27		
+3.9014494604562E-13						
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						
2	00:00:00	1	13	37	124	0
+6.2098836161097E-26				+4.2781604140423E-13		
+9.999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.999999999998E-01						

+1.00000000000001E+00, +1.00000000000001E+00, +9.9999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.9999999999998E-01						
2	00:00:00	1	14	38	126	0
+4.7389390548980E-26				+4.8196706324669E-13		
+9.9999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.9999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.9999999999998E-01						
2	00:00:00	1	15	37	120	0
+4.5780218133173E-26				+4.9812354105641E-13		
+9.9999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.9999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.9999999999998E-01						
2	00:00:00	1	16	38	127	0
+3.6733960938338E-26				+3.3692719887678E-13		
+9.9999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						
+1.00000000000001E+00, +1.00000000000001E+00, +9.9999999999997E-01,						
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,						
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,						
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,						
+9.9999999999998E-01						
2	00:00:00	1	17	35	119	0
+6.4893051219192E-26				+5.1985858289360E-13		
+9.9999999999998E-01, +9.9999999999963E-01, +9.9999999999957E-01,						
+9.9999999999949E-01, +9.9999999999967E-01, +1.00000000000001E+00,						
+1.00000000000001E+00, +9.9999999999995E-01, +9.9999999999998E-01,						
+9.9999999999965E-01, +1.00000000000005E+00, +1.00000000000005E+00,						
+1.00000000000001E+00, +1.00000000000000E+00, +9.9999999999990E-01,						


```
+1.00000000000001E+00, +1.00000000000001E+00, +9.999999999997E-01,
+1.00000000000000E+00, +1.00000000000000E+00, +1.00000000000000E+00,
+9.9999999999995E-01, +9.9999999999995E-01, +1.00000000000001E+00,
+1.00000000000000E+00, +1.00000000000001E+00, +1.00000000000000E+00,
+9.9999999999998E-01
```

The optimization routine failed to converge. This problem can sometimes be mitigated by choosing more reasonable initial parameter values, setting more conservative bounds, or configuring other optimization settings.

Optimization failed after 00:00:01.
Computing the Hessian and estimating standard errors ...
Computed results after 00:00:07.

Problem Results Summary:

=====					
=====					
GMM	Objective	Gradient	Hessian		
Hessian	Clipped	Weighting Matrix	Covariance Matrix		
Step	Value	Norm	Min Eigenvalue	Max	
Eigenvalue	Shares	Condition Number	Condition Number		

2	+3.1247090742030E-26	+4.1981634940432E-13	-6.4693617698989E-05		
+7.1284129245656E-05	0	+6.2384331654490E+02	+8.5572903008789E+19		
=====					
=====					

Cumulative Statistics:

=====					
Computation	Optimizer	Optimization	Objective	Fixed Point	Contraction
Time	Converged	Iterations	Evaluations	Iterations	Evaluations

00:00:27	No	2	28	3510	10852
=====					

Nonlinear Coefficient Estimates (Robust SEs in Parentheses):

=====				
=====				
=====				
=====				
=====				
=====				
Sigma:	1	prices	char1	
char2	char3	costsh1	costsh2	
Sigma Squared:	1	prices	char1	
char2	char3	costsh1	costsh2	

```

-----
----- | -----
-----
-----

1      +9.999999999998E-01
|      1      +9.999999999997E-01      +9.9999999999961E-01
+9.9999999999947E-01      +1.0000000000001E+00      +1.0000000000005E+00
+1.0000000000001E+00      +9.999999999993E-01
      (+2.5646592826311E-03)
|
      (+5.1293185652622E-03)      (+1.3207545868449E-01)
(+1.5058832748724E-01)      (+8.9404092204642E-02)      (+9.3373440200829E-02)
(+1.7107045772261E-01)      (+2.6340767802889E-01)
|
prices      +9.9999999999963E-01      +9.9999999999957E-01
|      prices      +9.9999999999961E-01      +1.9999999999984E+00
+1.9999999999984E+00      +1.999999999993E+00      +2.0000000000003E+00
+1.9999999999994E+00      +1.999999999991E+00
      (+1.3184999792281E-01)      (+1.3991843509955E-01)
|
      (+1.3207545868449E-01)      (+5.3590031997448E-01)
(+3.8885552172465E-01)      (+4.3424917372389E-01)      (+2.1839917494496E-01)
(+5.1392529984977E-01)      (+4.8697033740639E-01)
|
char1      +9.9999999999949E-01      +9.9999999999967E-01      +1.0000000000001E+00
|      char1      +9.9999999999947E-01      +1.9999999999984E+00
+2.9999999999985E+00      +2.999999999993E+00      +3.0000000000004E+00
+2.9999999999994E+00      +2.999999999992E+00
      (+1.4880232509789E-01)      (+8.0273493684577E-02)      (+9.4414289766014E-02)
|
      (+1.5058832748724E-01)      (+3.8885552172465E-01)
(+3.6269074507471E-01)      (+3.8084105778425E-01)      (+2.8790374275702E-01)
(+2.3897977261083E-01)      (+5.0303961256615E-01)
|
char2      +1.0000000000001E+00      +9.999999999995E-01      +9.999999999998E-01
+9.9999999999965E-01
|      char2      +1.0000000000001E+00      +1.999999999993E+00
+2.999999999993E+00      +3.999999999994E+00      +4.0000000000008E+00
+3.999999999998E+00      +3.999999999997E+00
      (+8.7941082407489E-02)      (+1.4071118102061E-01)      (+4.2451382594656E-02)
(+1.3039574930044E-01)
|
      (+8.9404092204642E-02)      (+4.3424917372389E-01)
(+3.8084105778425E-01)      (+7.3633613361793E-01)      (+2.4854032239524E-01)
(+4.8473258216525E-01)      (+4.4218389501217E-01)
|
char3      +1.0000000000005E+00      +1.0000000000005E+00      +1.0000000000001E+00
+1.0000000000000E+00      +9.999999999990E-01
|      char3      +1.0000000000005E+00      +2.0000000000003E+00
+3.0000000000004E+00      +4.0000000000008E+00      +5.0000000000021E+00
+5.0000000000012E+00      +5.0000000000011E+00
      (+9.5426665448296E-02)      (+1.1099111604828E-01)      (+1.6537543482697E-01)

```



```

[-0.55085592]
[-0.56303481]
[-2.15225778]
[-2.86799421]]
[[1. 0. 0. 0. 0. 0. 0.]
 [1. 1. 0. 0. 0. 0. 0.]
 [1. 1. 1. 0. 0. 0. 0.]
 [1. 1. 1. 1. 0. 0. 0.]
 [1. 1. 1. 1. 1. 0. 0.]
 [1. 1. 1. 1. 1. 1. 0.]
 [1. 1. 1. 1. 1. 1. 1.]]

```

1.e. Provide an explicit expression for the variance-covariance matrix of your estimates, and discuss how simulation error affects it.

```

[183]: results3_cov = pd.DataFrame(results3.parameter_covariances)
       print(results3_cov)

```

	0	1	2	3	4	5	6	\
0	0.001625	0.006537	0.025125	0.065225	0.030401	-0.029274	0.031231	
1	0.006537	4.293952	4.302209	0.314232	0.113451	-1.159126	1.101348	
2	0.025125	4.302209	4.835561	1.956313	0.986260	-1.732861	1.941210	
3	0.065225	0.314232	1.956313	5.469107	2.906676	-2.341999	2.428853	
4	0.030401	0.113451	0.986260	2.906676	1.591627	-1.134491	1.223724	
5	-0.029274	-1.159126	-1.732861	-2.341999	-1.134491	2.201772	-0.888219	
6	0.031231	1.101348	1.941210	2.428853	1.223724	-0.888219	1.910208	
7	0.057660	1.833390	3.264304	4.553202	2.302630	-2.288523	2.881109	
8	0.000791	1.169556	1.126886	0.065212	-0.010042	-0.652926	0.148581	
9	0.056135	2.397238	3.580147	3.990872	2.006543	-2.315535	2.476680	
10	-0.048687	-1.922865	-2.368904	-1.759663	-0.743116	1.462130	-1.205421	
11	-0.064725	-1.463398	-2.322486	-3.016845	-1.406388	1.774001	-1.765258	
12	-0.044718	-0.675702	-1.792690	-4.408653	-2.222433	3.693224	-1.279845	
13	-0.045929	0.589425	-0.681120	-4.395705	-2.290715	2.425964	-1.512774	
14	-0.009695	0.528634	0.133831	-1.604920	-0.838303	1.364510	-0.141741	
15	-0.044255	3.156325	1.913687	-3.133666	-1.750429	-1.008606	-1.638262	
16	-0.040716	2.972820	1.846746	-2.777120	-1.557138	-1.097925	-1.504849	
17	0.007546	0.272980	0.467612	0.665468	0.342117	-0.400281	0.352863	
18	0.009163	0.037604	0.338548	1.043295	0.546932	-0.631044	0.402680	
19	0.004235	-0.242256	-0.102985	0.351293	0.198142	0.089797	0.213553	
20	-0.003252	-0.043419	-0.151378	-0.395354	-0.206164	0.281848	-0.135488	
21	-0.038401	-2.446844	-3.626070	-5.294880	-2.655337	5.859947	-1.301978	
22	-0.034888	-2.341269	-3.410529	-4.855273	-2.429463	5.474742	-1.175007	
23	-0.004949	0.003678	-0.057309	-0.141531	-0.067825	-0.083358	-0.153364	
24	-0.001956	-0.405537	-0.390187	-0.058574	-0.009977	0.285681	-0.025659	
25	-0.005055	0.151606	0.089393	-0.053596	-0.029830	-0.338742	-0.185900	
26	-0.003472	0.035177	-0.081011	-0.390399	-0.207578	0.199150	-0.148903	
27	-0.001639	-0.159239	-0.235506	-0.383542	-0.193347	0.492592	-0.045827	
28	0.013635	4.634001	4.934335	1.185445	0.594246	-1.429526	1.683661	
29	0.072356	0.986000	2.844016	6.401705	3.414889	-3.155520	2.730571	

30	0.060550	2.360282	4.205826	5.854666	2.993545	-3.145988	3.669605
31	-0.081578	-1.208150	-1.786713	-1.761148	-0.659836	0.246470	-1.713496
32	-0.065609	4.370627	2.543022	-4.674718	-2.599999	-1.282539	-2.441129
33	-0.060148	-3.549730	-5.377535	-8.041879	-4.043283	8.610663	-2.081699

	7	8	9	...	24	25	26	27 \
0	0.057660	0.000791	0.056135	...	-0.001956	-0.005055	-0.003472	-0.001639
1	1.833390	1.169556	2.397238	...	-0.405537	0.151606	0.035177	-0.159239
2	3.264304	1.126886	3.580147	...	-0.390187	0.089393	-0.081011	-0.235506
3	4.553202	0.065212	3.990872	...	-0.058574	-0.053596	-0.390399	-0.383542
4	2.302630	-0.010042	2.006543	...	-0.009977	-0.029830	-0.207578	-0.193347
5	-2.288523	-0.652926	-2.315535	...	0.285681	-0.338742	0.199150	0.492592
6	2.881109	0.148581	2.476680	...	-0.025659	-0.185900	-0.148903	-0.045827
7	4.890510	0.464468	4.385462	...	-0.163979	-0.073260	-0.308801	-0.317627
8	0.464468	0.445124	0.661046	...	-0.168965	0.165019	-0.006892	-0.153018
9	4.385462	0.661046	4.199754	...	-0.255128	0.000437	-0.254887	-0.334154
10	-2.265049	-0.585183	-2.485594	...	0.260699	0.014439	0.078719	0.161280
11	-3.207016	-0.417269	-3.176785	...	0.204011	0.097503	0.170447	0.191032
12	-3.659117	-0.796811	-3.473419	...	0.374819	-0.613231	0.402446	0.891077
13	-3.369697	-0.100447	-2.827373	...	0.085807	-0.208868	0.371262	0.532934
14	-0.965147	-0.160943	-0.810933	...	0.095682	-0.306758	0.174394	0.390548
15	-1.845625	1.447917	-0.719684	...	-0.557595	0.779719	0.187301	-0.429655
16	-1.607376	1.391905	-0.560559	...	-0.538172	0.765104	0.158660	-0.444743
17	0.667629	0.093925	0.620327	...	-0.037033	0.021758	-0.048606	-0.072839
18	0.873108	0.078986	0.753338	...	-0.036547	0.069206	-0.089207	-0.142420
19	0.251349	-0.132236	0.132957	...	0.053746	-0.080715	-0.020547	0.042947
20	-0.330159	-0.051181	-0.296815	...	0.022987	-0.042000	0.035314	0.067555
21	-4.747676	-1.797835	-4.874613	...	0.772879	-1.261742	0.531638	1.517863
22	-4.375954	-1.703983	-4.518373	...	0.731358	-1.190591	0.490366	1.421377
23	-0.159202	0.056768	-0.127487	...	-0.022106	0.072348	-0.000615	-0.048964
24	-0.163979	-0.168965	-0.255128	...	0.069246	-0.068253	0.004862	0.066288
25	-0.073260	0.165019	0.000437	...	-0.068253	0.150186	-0.015139	-0.123607
26	-0.308801	-0.006892	-0.254887	...	0.004862	-0.015139	0.032684	0.043616
27	-0.317627	-0.153018	-0.334154	...	0.066288	-0.123607	0.043616	0.137166
28	2.735584	1.200271	3.171575	...	-0.404945	0.105406	-0.020954	-0.184703
29	5.390968	0.347227	4.901551	...	-0.175681	0.092422	-0.465018	-0.577466
30	6.324197	0.687308	5.583490	...	-0.227217	0.042736	-0.427522	-0.518958
31	-2.322752	0.029236	-2.402519	...	0.038799	0.608749	-0.005710	-0.327040
32	-2.848033	2.015741	-1.241121	...	-0.775266	1.096274	0.282225	-0.582249
33	-7.204460	-2.592059	-7.332985	...	1.115226	-1.808972	0.795536	2.212190

	28	29	30	31	32	33
0	0.013635	0.072356	0.060550	-0.081578	-0.065609	-0.060148
1	4.634001	0.986000	2.360282	-1.208150	4.370627	-3.549730
2	4.934335	2.844016	4.205826	-1.786713	2.543022	-5.377535
3	1.185445	6.401705	5.854666	-1.761148	-4.674718	-8.041879
4	0.594246	3.414889	2.993545	-0.659836	-2.599999	-4.043283
5	-1.429526	-3.155520	-3.145988	0.246470	-1.282539	8.610663

6	1.683661	2.730571	3.669605	-1.713496	-2.441129	-2.081699
7	2.735584	5.390968	6.324197	-2.322752	-2.848033	-7.204460
8	1.200271	0.347227	0.687308	0.029236	2.015741	-2.592059
9	3.171575	4.901551	5.583490	-2.402519	-1.241121	-7.332985
10	-2.182505	-2.237446	-2.554063	2.733128	-0.572666	3.847288
11	-1.911046	-3.573607	-3.733153	3.225490	1.415680	4.727002
12	-1.125759	-5.767854	-5.207991	-0.556063	-0.808843	15.200772
13	0.045620	-5.247973	-4.606672	0.163070	2.931613	9.586299
14	0.437732	-2.094585	-1.559621	-1.042414	-0.087876	6.267674
15	2.590839	-2.594269	-1.935009	2.310893	10.395048	-5.739507
16	2.457645	-2.212195	-1.619857	2.269410	9.827562	-6.065444
17	0.391004	0.823860	0.885637	-0.200549	-0.202089	-1.430222
18	0.185777	1.281073	1.222963	0.052191	-0.456763	-2.543752
19	-0.166722	0.308779	0.287236	-0.236494	-1.044304	0.543970
20	-0.094833	-0.503648	-0.472981	-0.064596	0.045866	1.169754
21	-2.957286	-7.588814	-7.182399	-2.382362	-5.556556	25.164128
22	-2.802350	-6.999528	-6.637352	-2.258583	-5.395718	23.534621
23	-0.034504	-0.097785	-0.124754	0.412807	0.544900	-0.638996
24	-0.404945	-0.175681	-0.227217	0.038799	-0.775266	1.115226
25	0.105406	0.092422	0.042736	0.608749	1.096274	-1.808972
26	-0.020954	-0.465018	-0.427522	-0.005710	0.282225	0.795536
27	-0.184703	-0.577466	-0.518958	-0.327040	-0.582249	2.212190
28	5.187265	1.997688	3.550095	-1.498578	3.529799	-4.355901
29	1.997688	7.721319	7.040875	-1.608728	-3.968287	-11.409915
30	3.550095	7.040875	8.457279	-1.880133	-3.047115	-10.819213
31	-1.498578	-1.608728	-1.880133	5.922008	3.357589	-3.289193
32	3.529799	-3.968287	-3.047115	3.357589	14.783728	-7.613216
33	-4.355901	-11.409915	-10.819213	-3.289193	-7.613216	36.812617

[34 rows x 34 columns]

2. Compare the cross and own-price elasticities for market 10 for the RC logit and pure logit model.

```
[185]: elasticities2 = results3.compute_elasticities()
elasticities2_market_10 = pd.DataFrame(elasticities2[data.market_ids == 10])
elasticities2_market_10 = elasticities2_market_10.dropna(axis=1, how='all')

print(elasticities_market_10)
```

Computing elasticities with respect to prices ...

Finished after 00:00:00.

	0	1	2	3	4	5	6	\
0	-3.791656	0.591234	0.076763	0.038112	0.245743	0.209206	0.037551	
1	0.065788	-3.422239	0.076763	0.038112	0.245743	0.209206	0.037551	
2	0.065788	0.591234	-5.220499	0.038112	0.245743	0.209206	0.037551	
3	0.065788	0.591234	0.076763	-3.584304	0.245743	0.209206	0.037551	
4	0.065788	0.591234	0.076763	0.038112	-4.433488	0.209206	0.037551	

5	0.065788	0.591234	0.076763	0.038112	0.245743	-3.041279	0.037551
6	0.065788	0.591234	0.076763	0.038112	0.245743	0.209206	-5.773704
7	0.065788	0.591234	0.076763	0.038112	0.245743	0.209206	0.037551
8	0.065788	0.591234	0.076763	0.038112	0.245743	0.209206	0.037551
9	0.065788	0.591234	0.076763	0.038112	0.245743	0.209206	0.037551
10	0.065788	0.591234	0.076763	0.038112	0.245743	0.209206	0.037551

	7	8	9	10
0	0.011711	0.377774	0.024602	0.009697
1	0.011711	0.377774	0.024602	0.009697
2	0.011711	0.377774	0.024602	0.009697
3	0.011711	0.377774	0.024602	0.009697
4	0.011711	0.377774	0.024602	0.009697
5	0.011711	0.377774	0.024602	0.009697
6	0.011711	0.377774	0.024602	0.009697
7	-5.278629	0.377774	0.024602	0.009697
8	0.011711	-3.271287	0.024602	0.009697
9	0.011711	0.377774	-6.355967	0.009697
10	0.011711	0.377774	0.024602	-4.709363

3. We are assuming here that demand in all markets is identical. With data on the distribution of income within each market, how could you let the distribution of α_i (the random variable coefficient on price) vary systematically across markets?

Uma possibilidade seria estimar uma variável γ que captura como a renda afeta a distribuição de α_i dos consumidores em cada mercado, ou seja, a sensibilidade dos consumidores ao preço.

$$\alpha_i = \alpha + \gamma Renda + \varepsilon$$