The Price of Basic Goods

CS146 LBA

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```
import pystan
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import scipy.stats as sts
```

Data Preprocessing

```
# I a lot of preprocessing in google sheets which was dropping all the names, emails, addresses, converting the cu
dataset = pd.read_csv('https://raw.githubusercontent.com/marcelaradilla/cs146/a1f148c65ba17534d0bcbf900c40ed684ce0
```

```
dataset.head()
```

	Country	Store	Perception	Rent	P1M1	P1M2	P1M3	P2M1	P2M2	P2M3	P3M1	P3M2	P3M3
0	Germany	EDEKA	Mid-range	1071.00	3.4867	1.9159	2.082500	2.0587	2.0587	0.0000	5.80125	5.331200	3.37960
1	Germany	EDEKA	Mid-range	1011.50	2.3205	3.4867	4.358375	2.0587	1.3209	2.0587	3.37960	5.807200	5.75960
2	Germany	EDEKA	Mid-range	1190.00	3.4867	1.4875	2.034900	2.7965	1.7374	0.0000	2.28480	11.622333	13.94680
3	Germany	Alnatura	Luxury (expensive)	1190.00	4.7481	4.7481	4.748100	2.7251	0.0000	0.0000	9.40100	7.128100	11.78100
4	Germany	EDEKA	Budget (cheap)	1065.05	3.4867	3.4867	3.486700	2.0587	1.3209	4.6172	7.25900	5.759600	5.80125

We will now reshape the dataset to have one row per price observation, meaning that for each row of the original dataset, we will take the first 4 columns, make 30 copies of it, and for each row (1:30) we will add the price observation. We will keep track of which column those observations are coming from so that we add an extra column for what kind of product that observation is coming from.

```
#in this cell we iterate through the 64 responses to the form and we add the price from each of the 30 price colum
all_data = []
for i in range(64):
  for j in range(30):
    all_data.append(np.concatenate((dataset.iloc[i][:4], [dataset.iloc[i][4:][j]], [dataset.iloc[i][4:].index[j][1
    #to encode the product column, we take from the second character to the character that is before the last two
    #example: from the column title P1M1, [1:-2], takes only 1.
#in the end we have a dataframe with the colums: 'country','store','perception','rent','price','product'
df = pd.DataFrame(all_data, columns=['country','store','perception','rent','price','product'])
```

```
#making sure that we have no repetitions
#NOTE: The store named Market was given because a student did not put the name of the store and it did not come up
#when we looked the address up on Google Maps
np.unique(df.store)
```

```
array(['ALDI', 'Albertsons', 'Alnatura', 'Big C', 'Carrefour', 'Chung cu',
       'Coupang', 'EDEKA', 'Epicerie', 'Foodsco', 'Grocery Outlet',
       'Latorre', 'Lidl', 'Marjane', 'Market', 'Nam An', 'REWE',
       'Safeway', 'Sainsburys', 'Smiths', 'Target', 'Tesco',
       'Trader Joes', 'Vons', 'Waitrose', 'Walmart', 'Whole Foods'],
      dtype=object)
```

```
np.unique(df.country)
```

```
array(['Germany', 'Guatemala', 'Morocco', 'South Korea', 'UK', 'USA',
       'Vietnam'], dtype=object)
```

We will now encode the country and the perception characteristics into numbers in a column.

```
df['perception_code'] = pd.factorize(df['perception'], sort=True)[0] + 1
df['country_code'] = pd.factorize(df['country'], sort=True)[0] + 1
```

```
df
```

	country	store	perception	rent	price	product	perception_code	country_code
0	Germany	EDEKA	Mid-range	1071.0	3.486700	1	3	1
1	Germany	EDEKA	Mid-range	1071.0	1.915900	1	3	1
2	Germany	EDEKA	Mid-range	1071.0	2.082500	1	3	1
3	Germany	EDEKA	Mid-range	1071.0	2.058700	2	3	1
4	Germany	EDEKA	Mid-range	1071.0	2.058700	2	3	1
...	...	...	...	...	...	...	...	...
1915	Vietnam	Chung cu	Mid-range	500.0	0.111667	9	3	7
1916	Vietnam	Chung cu	Mid-range	500.0	0.111667	9	3	7
1917	Vietnam	Chung cu	Mid-range	500.0	4.480000	10	3	7
1918	Vietnam	Chung cu	Mid-range	500.0	3.800000	10	3	7
1919	Vietnam	Chung cu	Mid-range	500.0	4.660000	10	3	7

1920 rows × 8 columns

```
#from google sheets, all missing observations were replaced with zero
#we are now removing all missing observations, knowing that we are not removing
#anything that is actually zero because there are no zeros as price observations
df = df[(df != 0).all(1)]
```

```
df
```

	country	store	perception	rent	price	product	perception_code	country_code
0	Germany	EDEKA	Mid-range	1071.0	3.486700	1	3	1
1	Germany	EDEKA	Mid-range	1071.0	1.915900	1	3	1
2	Germany	EDEKA	Mid-range	1071.0	2.082500	1	3	1
3	Germany	EDEKA	Mid-range	1071.0	2.058700	2	3	1
4	Germany	EDEKA	Mid-range	1071.0	2.058700	2	3	1
...	...	...	...	...	...	...	...	...
1915	Vietnam	Chung cu	Mid-range	500.0	0.111667	9	3	7
1916	Vietnam	Chung cu	Mid-range	500.0	0.111667	9	3	7
1917	Vietnam	Chung cu	Mid-range	500.0	4.480000	10	3	7
1918	Vietnam	Chung cu	Mid-range	500.0	3.800000	10	3	7
1919	Vietnam	Chung cu	Mid-range	500.0	4.660000	10	3	7

1761 rows × 8 columns

```
df_cleancopy=df
```

```
#checking that we have no zeroes in our data
np.min(df.price)
```

```
0.00143
```

```
#the product column was made from strings, we make it all integers
df['product'] = df['product'].apply(lambda x: int(x))
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#r
```

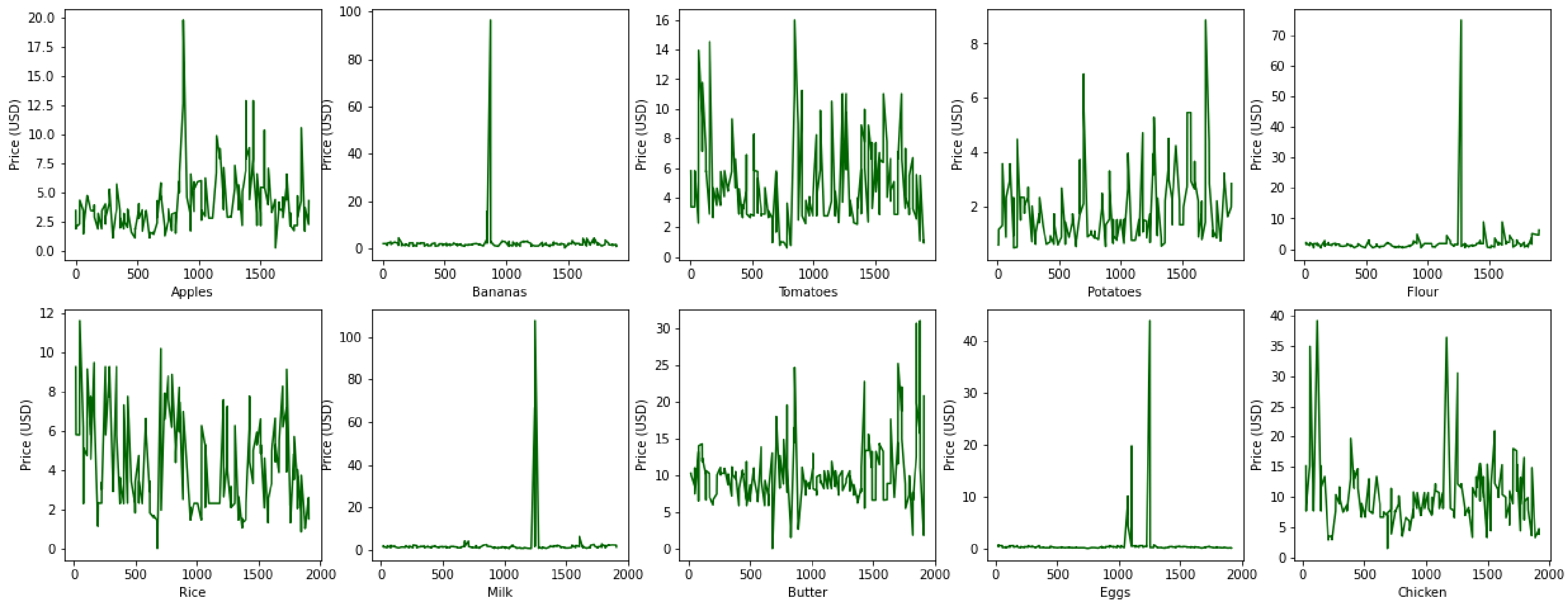
```
df['product'].values
```

```
array([ 1,  1,  1, ..., 10, 10, 10])
```

Plotting the data to look at the range of prices and outliers.

```
products=['Apples','Bananas','Tomatoes','Potatoes','Flour','Rice','Milk','Butter','Eggs','Chicken']
```

```
prods=[1,2,3,4,5,6,7,8,9,10]
mins=[]
maxs=[]
fig, axs = plt.subplots(2, 5, figsize=(21,8))
x=0
for line in range(2):
  for el in range(5):
    axs[line,el].plot(df.loc[df['product'] == prods[x]]['price'], color='darkgreen')
    mins.append(np.min(df.loc[df['product'] == prods[x]]['price']))
    maxs.append(np.max(df.loc[df['product'] == prods[x]]['price']))
    #print(x)
    axs[line,el].set_xlabel(products[x])
    axs[line,el].set_ylabel('Price (USD)')
    x=x+1
  x=5
```



As we can see there are some very extreme outliers, my guess is there are due to errors when plugging data collected into the form. It will be really hard to go through all of the outliers and remove them, and removing data is also adding bias to the analysis, so I will try my best to remove those that are completely unrealistic and that in my opinion are probably due to error.

```
print('Mins:',mins)
print('Maxs:',maxs)
```

```
Mins: [0.2725450902, 0.3044244295, 0.605, 0.4648933333, 0.40645, 0.00143, 0.5814977974000001, 0.0122086956499
Maxs: [19.8, 96.36, 15.9844, 8.866666667, 74.844, 11.62233333, 107.448, 30.96, 43.956, 39.150999999999996]
```

```
#I am removing this price for bananas because it is just unrealistic, and because there are also other observation
df.loc[df['price'] == 96.36]
```

	country	store	perception	rent	price	product	perception_code	country_code
873	UK	Sainsburys	Mid-range	1030.92	96.36	2	3	5

```
df.loc[870:875]
```

	country	store	perception	rent	price	product	perception_code	country_code
870	UK	Sainsburys	Mid-range	1030.92	12.672000	1	3	5
871	UK	Sainsburys	Mid-range	1030.92	12.672000	1	3	5
872	UK	Sainsburys	Mid-range	1030.92	19.800000	1	3	5
873	UK	Sainsburys	Mid-range	1030.92	96.360000	2	3	5
874	UK	Sainsburys	Mid-range	1030.92	2.346667	2	3	5
875	UK	Sainsburys	Mid-range	1030.92	2.904000	2	3	5

```
df=df.drop(873)
```

```
df.loc[870:875]
```

	country	store	perception	rent	price	product	perception_code	country_code
870	UK	Sainsburys	Mid-range	1030.92	12.672000	1	3	5
871	UK	Sainsburys	Mid-range	1030.92	12.672000	1	3	5
872	UK	Sainsburys	Mid-range	1030.92	19.800000	1	3	5
874	UK	Sainsburys	Mid-range	1030.92	2.346667	2	3	5
875	UK	Sainsburys	Mid-range	1030.92	2.904000	2	3	5

```
#also removing this price for flour from Waitrose
df.loc[df['price'] == 74.844]
```

	country	store	perception	rent	price	product	perception_code	country_code
1272	UK	Waitrose	Luxury (expensive)	3003.0	74.844	5	2	5

```
df.loc[1269:1275]
```

	country	store	perception	rent	price	product	perception_code	country_code
1269	UK	Waitrose	Luxury (expensive)	3003.0	3.9600	4	2	5
1270	UK	Waitrose	Luxury (expensive)	3003.0	3.1680	4	2	5
1271	UK	Waitrose	Luxury (expensive)	3003.0	5.2800	4	2	5
1272	UK	Waitrose	Luxury (expensive)	3003.0	74.8440	5	2	5
1273	UK	Waitrose	Luxury (expensive)	3003.0	1.5840	5	2	5
1274	UK	Waitrose	Luxury (expensive)	3003.0	0.8844	5	2	5
1275	UK	Waitrose	Luxury (expensive)	3003.0	2.1120	6	2	5

```
df=df.drop(1272)
```

```
#Taking out two milk outliers (107 and 66 USD)
df.loc[df['price'] == 107.448]
```

	country	store	perception	rent	price	product	perception_code	country_code
1250	UK	Waitrose	Luxury (expensive)	3718.44	107.448	7	2	5

```
df.loc[1245:1257]
```

	country	store	perception	rent	price	product	perception_code	country_code
1245	UK	Waitrose	Luxury (expensive)	3718.44	4.488	6	2	5
1246	UK	Waitrose	Luxury (expensive)	3718.44	7.260	6	2	5
1247	UK	Waitrose	Luxury (expensive)	3718.44	3.960	6	2	5
1248	UK	Waitrose	Luxury (expensive)	3718.44	66.792	7	2	5
1249	UK	Waitrose	Luxury (expensive)	3718.44	1.518	7	2	5
1250	UK	Waitrose	Luxury (expensive)	3718.44	107.448	7	2	5
1251	UK	Waitrose	Luxury (expensive)	3718.44	10.560	8	2	5
1252	UK	Waitrose	Luxury (expensive)	3718.44	8.976	8	2	5
1253	UK	Waitrose	Luxury (expensive)	3718.44	7.920	8	2	5
1254	UK	Waitrose	Luxury (expensive)	3718.44	43.956	9	2	5
1255	UK	Waitrose	Luxury (expensive)	3718.44	29.700	9	2	5
1256	UK	Waitrose	Luxury (expensive)	3718.44	0.220	9	2	5
1257	UK	Waitrose	Luxury (expensive)	3718.44	30.492	10	2	5

```
df=df.drop(1250)
```

```
df=df.drop(1248)
```

```
#egg outlier
df.loc[df['price'] == 43.956]
```

	country	store	perception	rent	price	product	perception_code	country_code
1254	UK	Waitrose	Luxury (expensive)	3718.44	43.956	9	2	5

```
df=df.drop(1254)
```

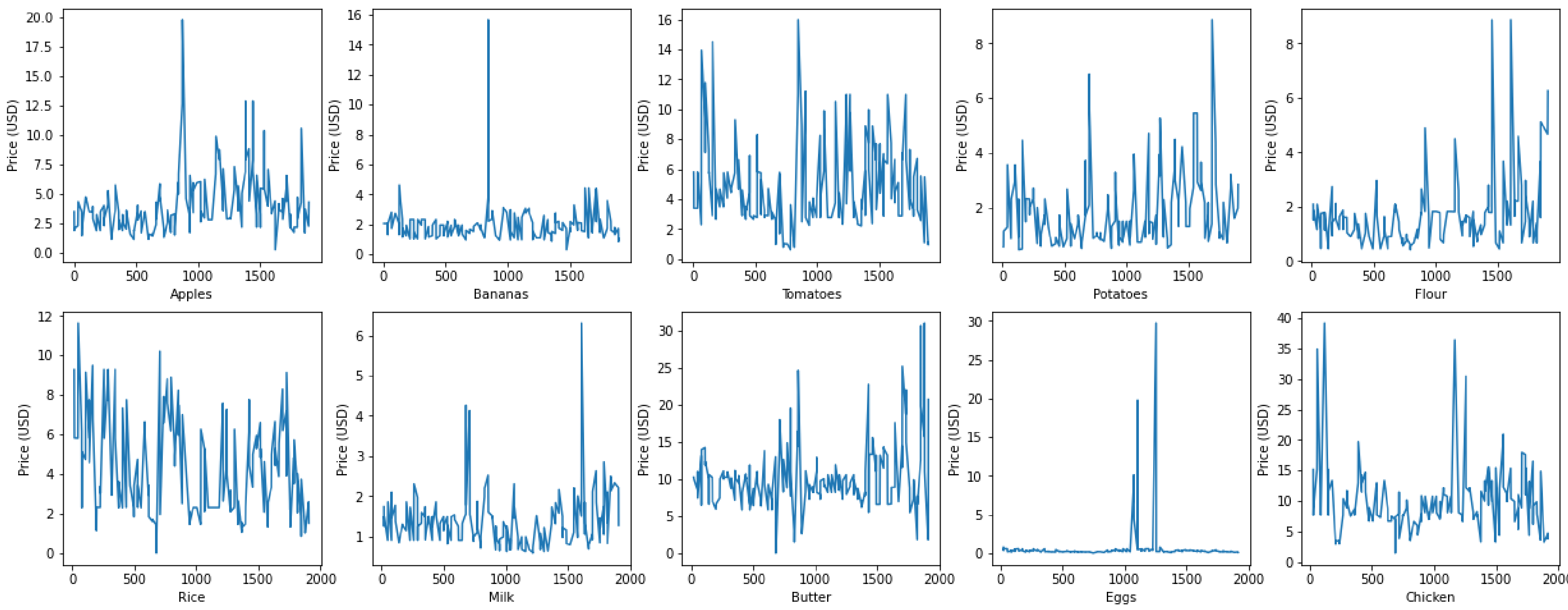
```
df
```

	country	store	perception	rent	price	product	perception_code	country_code
0	Germany	EDEKA	Mid-range	1071.0	3.486700	1	3	1
1	Germany	EDEKA	Mid-range	1071.0	1.915900	1	3	1
2	Germany	EDEKA	Mid-range	1071.0	2.082500	1	3	1
3	Germany	EDEKA	Mid-range	1071.0	2.058700	2	3	1
4	Germany	EDEKA	Mid-range	1071.0	2.058700	2	3	1
...	...	...	...	...	...	...	...	...
1915	Vietnam	Chung cu	Mid-range	500.0	0.111667	9	3	7
1916	Vietnam	Chung cu	Mid-range	500.0	0.111667	9	3	7
1917	Vietnam	Chung cu	Mid-range	500.0	4.480000	10	3	7
1918	Vietnam	Chung cu	Mid-range	500.0	3.800000	10	3	7
1919	Vietnam	Chung cu	Mid-range	500.0	4.660000	10	3	7

1756 rows × 8 columns

We took 5 outlier values in total, we will now plot the data again.

```
products=['Apples','Bananas','Tomatoes','Potatoes','Flour','Rice','Milk','Butter','Eggs','Chicken']
prods=[1,2,3,4,5,6,7,8,9,10]
mins=[]
maxs=[]
fig, axs = plt.subplots(2, 5, figsize=(21,8))
x=0
for line in range(2):
  for el in range(5):
    axs[line,el].plot(df.loc[df['product'] == prods[x]]['price'])
    mins.append(np.min(df.loc[df['product'] == prods[x]]['price']))
    maxs.append(np.max(df.loc[df['product'] == prods[x]]['price']))
    #print(x)
    axs[line,el].set_xlabel(products[x])
    axs[line,el].set_ylabel('Price (USD)')
    x=x+1
  x=5
```




```
print('Mins:',mins)
print('Maxs:',maxs)
```

```
Mins: [0.2725450902, 0.3044244295, 0.605, 0.4648933333, 0.40645, 0.00143, 0.5814977974000001, 0.0122086956499
Maxs: [19.8, 15.664000000000001, 15.9844, 8.866666667, 8.866666667, 11.62233333, 6.305263158, 30.96, 29.7, 39
```

As we can see we still have some outliers but we do not want to remove anymore since we want to avoid adding a self-generated bias to the observations that we are working with.

Building the model

Distributions:

We will use a truncated Cauchy for the prior for the base price, since the fat tails of distribution allow for higher probabilities of values far away from the mean than the normal distribution. We also do not have particular prior knowledge about, we could have looked up average prices of each product, but this dataset includes information from different countries and different types of stores so we kept the prior not very informative.

We will center the Cauchy around 5, assuming that most products cost around 5 USD.

We will use Gamma priors for the country and store type multipliers. Since the mean is given my the multiplication of the location and scale parameters of the distribution, we can know that it will be centered around 1 if we set them at 2 and 0.5. We will also use a Gamma(1,1) for the error, this is only to derive the standard distribution for the likelihood, since I know that some of the outliers are due to human error.

We will use a normal for the likelihood, setting the price to come from a normal distribution, whose mean is given by:

$(baseprice) * (country\ multiplier) * (store\ multiplier)$

and whose standard deviation is given by the error, over which we are also computing a posterior.

[ ] ↳ *2 cells hidden*

Providing STAN with the data

```
#creating a dictionary with our dataset
data={
    'n':len(df['price']),
    'p':len(np.unique(df['product'])),
    'c':len(np.unique(df['country'])),
    's':len(np.unique(df['perception_code'])),

    'prices':df['price'].values,
    'products':df['product'].values,
    'countries':df['country_code'].values,
    'stores':df['perception_code'].values
}
data
```

```
{'c': 7,
 'countries': array([1, 1, 1, ..., 7, 7, 7]),
 'n': 1756,
 'p': 10,
 'prices': array([3.4867, 1.9159, 2.0825, ..., 4.48  , 3.8   , 4.66  ]),
 'products': array([ 1,  1,  1, ..., 10, 10, 10]),
 's': 3,
 'stores': array([3, 3, 3, ..., 3, 3, 3])}
```

```
print(data)
```

```
{'n': 1756, 'p': 10, 'c': 7, 's': 3, 'prices': array([3.4867, 1.9159, 2.0825, ..., 4.48  , 3.8   , 4.66  ]),
```

Results

STAN output

```
#stan output
stan_results=stan_model.sampling(data=data)
samples=stan_results.extract()
print(stan_results)
```

```
Inference for Stan model: anon_model_48c5a5a4637074737e2ceedef0130919.
4 chains, each with iter=2000; warmup=1000; thin=1;
post-warmup draws per chain=1000, total post-warmup draws=4000.
```

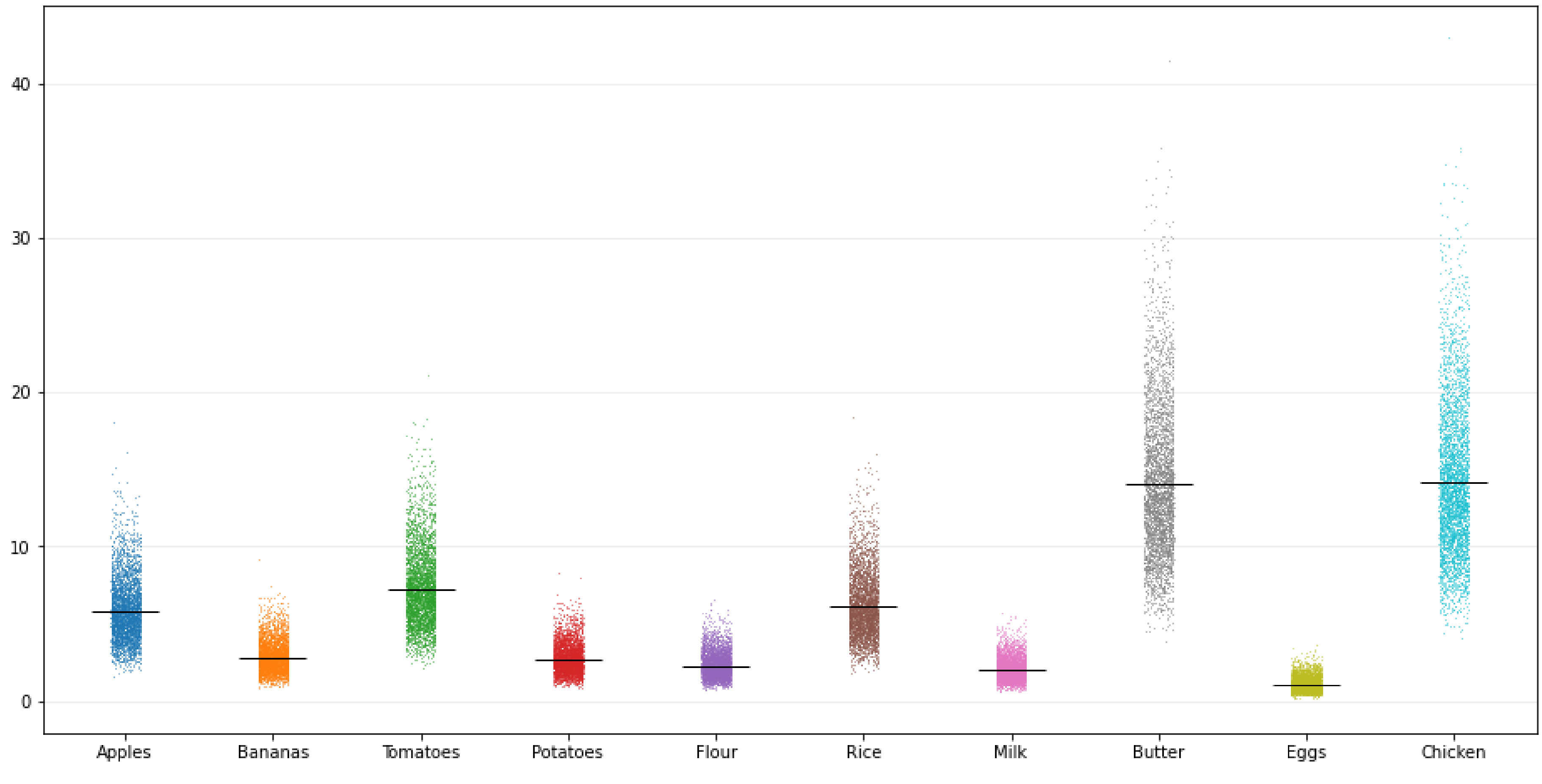
```
                 mean se_mean     sd   2.5%    25%    50%    75%  97.5%  n_eff   Rhat
base_price[1]    5.78    0.07   1.97   2.75   4.38   5.49   6.83  10.39    792   1.01
base_price[2]     2.8    0.03   0.99   1.29   2.09   2.66   3.34   5.14    846    1.0
base_price[3]    7.24    0.09   2.45   3.52   5.48   6.89   8.58  13.01    758   1.01
base_price[4]    2.67    0.03   0.94   1.24   2.01   2.53   3.19   4.93    828   1.01
base_price[5]    2.28    0.03   0.83   1.03   1.68   2.15   2.74   4.22    829   1.01
base_price[6]    6.11    0.07   2.08   2.96   4.64   5.78   7.26  11.04    804   1.01
base_price[7]    1.99    0.02   0.74   0.89   1.44   1.87   2.42   3.71    922    1.0
base_price[8]   14.02    0.17   4.74   6.78  10.63  13.28  16.59  24.98    773   1.01
base_price[9]    1.03    0.01   0.46   0.35    0.7   0.96   1.28   2.13   1052   1.01
base_price[10]  14.14    0.17   4.78   6.86  10.68  13.42  16.81  25.33    771   1.01
country_mult[1]  2.54    0.03   0.87   1.16   1.89   2.43   3.06   4.48    932    1.0
country_mult[2]  2.04    0.02   0.71   0.93   1.51   1.94   2.47   3.69    957    1.0
country_mult[3]  1.77    0.02   0.61   0.79   1.33   1.69   2.13   3.16    952    1.0
country_mult[4]  3.45    0.04   1.19   1.56   2.56    3.3   4.16   6.19    972    1.0
country_mult[5]  2.45    0.03   0.84    1.1   1.83   2.35   2.96    4.4    944    1.0
country_mult[6]  2.75    0.03   0.94   1.24   2.05   2.64    3.3   4.89    937    1.0
country_mult[7]  2.37    0.03   0.82   1.08   1.76   2.28   2.85   4.22    974    1.0
store_mult[1]    0.28  5.3e-3   0.14    0.1   0.19   0.25   0.35   0.63    713    1.0
store_mult[2]    0.46  8.6e-3   0.23   0.17    0.3   0.41   0.56   1.01    709    1.0
store_mult[3]    0.35  6.7e-3   0.18   0.13   0.23   0.32   0.43   0.79    707    1.0
error             2.8  9.6e-4   0.05    2.7   2.76   2.79   2.83   2.89   2431    1.0
lp__            -2680    0.08   3.23  -2687  -2683  -2680  -2678  -2675   1518    1.0

Samples were drawn using NUTS at Sun Nov  8 15:11:31 2020.
For each parameter, n_eff is a crude measure of effective sample size,
and Rhat is the potential scale reduction factor on split chains (at
convergence, Rhat=1).
```

Base prices for each product

```
products_1=['Apples','Bananas','Tomatoes','Potatoes','Flour','Rice','Milk','Butter','Eggs','Chicken']
plt.figure(figsize=(16,8))
for i in range(10):
      #this part was taken from the code Prof. Scheffler shared with us on session 7.2 when we were modeling elect
      #I thought it was a great way to show Stan output
  plt.plot(sts.uniform.rvs(loc=i-0.1, scale=0.2, size=4000), samples['base_price'][:,i], ',', alpha=0.5)
  plt.xticks([0,1,2,3,4,5,6,7,8,9],products_1)

plt.plot(range(0, 10),samples['base_price'].mean(axis=0), marker='_',linewidth=0,color="black",alpha=1,markersize=
plt.grid(True, alpha=0.25, axis='y')
plt.show()
```

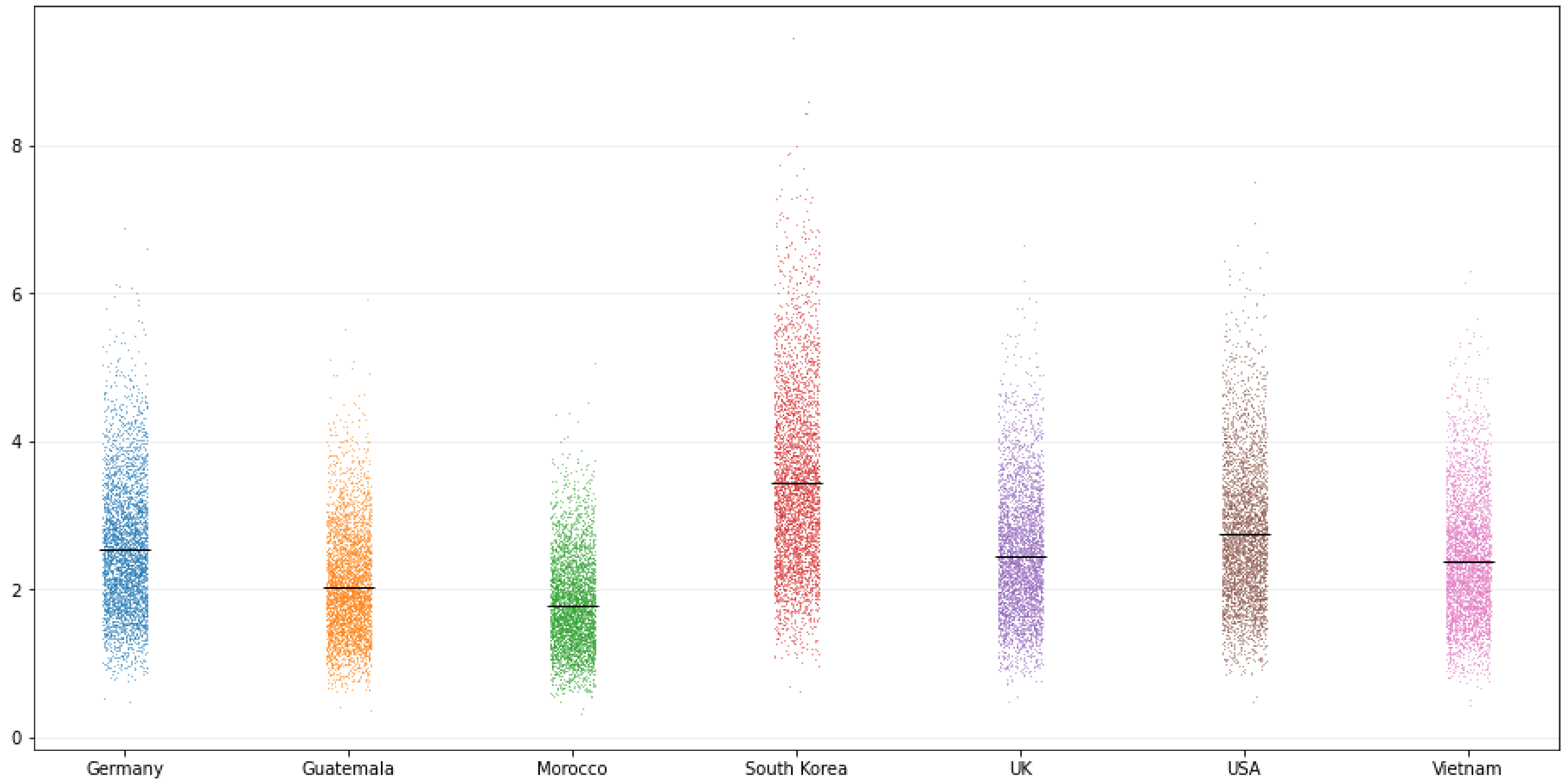


Country multipliers

```
countries_1=np.unique(df.country)
plt.figure(figsize=(16,8))
for i in range(7):
      #this part was taken from the code Prof. Scheffler shared with us on session 7.2 when we were modeling elect
      #I thought it was a great way to show Stan output
  plt.plot(sts.uniform.rvs(loc=i-0.1, scale=0.2, size=4000), samples['country_mult'][:,i], ',', alpha=0.5)
  plt.xticks([0,1,2,3,4,5,6],countries_1)

plt.plot(range(0, 7),samples['country_mult'].mean(axis=0), marker='_',linewidth=0,color="black",alpha=1,markersize
plt.grid(True, alpha=0.25, axis='y')
```

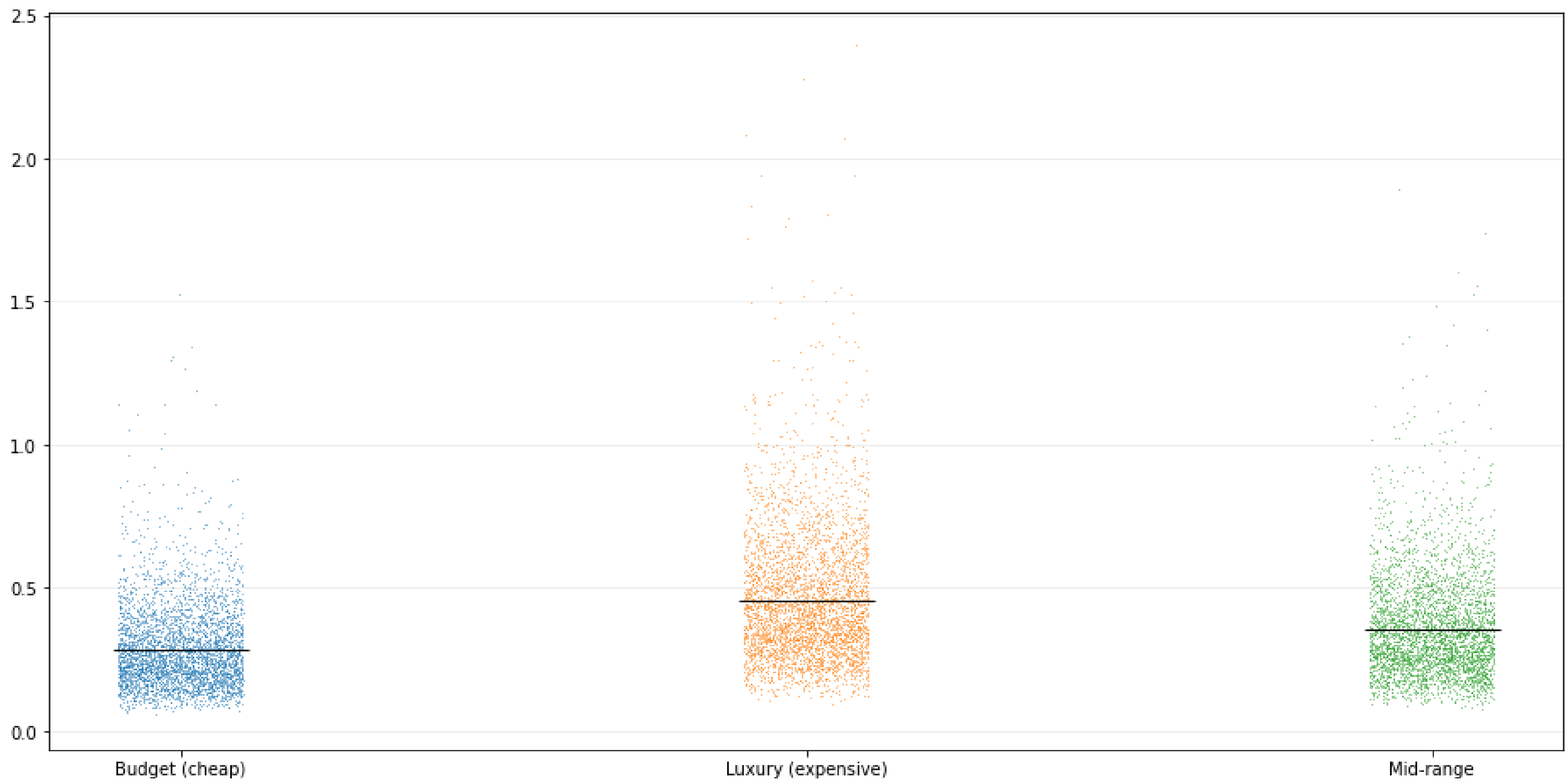
```
plt.show()
```



Store perception multipliers

```
perceptions_1=np.unique(df.perception)
plt.figure(figsize=(16,8))
for i in range(3):
      #this part was taken from the code Prof. Scheffler shared with us on session 7.2 when we were modeling elect
      #I thought it was a great way to show Stan output
  plt.plot(sts.uniform.rvs(loc=i-0.1, scale=0.2, size=4000), samples['store_mult'][:,i], ',', alpha=0.5)
  plt.xticks([0,1,2],perceptions_1)

plt.plot(range(0, 3),samples['store_mult'].mean(axis=0), marker='_',linewidth=0,color="black",alpha=1,markersize=8
plt.grid(True, alpha=0.25, axis='y')
plt.show()
```



Rental prices

In this section we focus on analyzing the correlation between the variation in price by geographical location and the variation in rental prices. We begin by taking the mean of the rental price data for each country.

```
rental_prices=[]
for country in np.unique(df['country']):
  countryrental=np.mean(df.loc[df['country'] == country]['rent'].values)
  rental_prices.append(countryrental)
  print(country,':',countryrental)
```

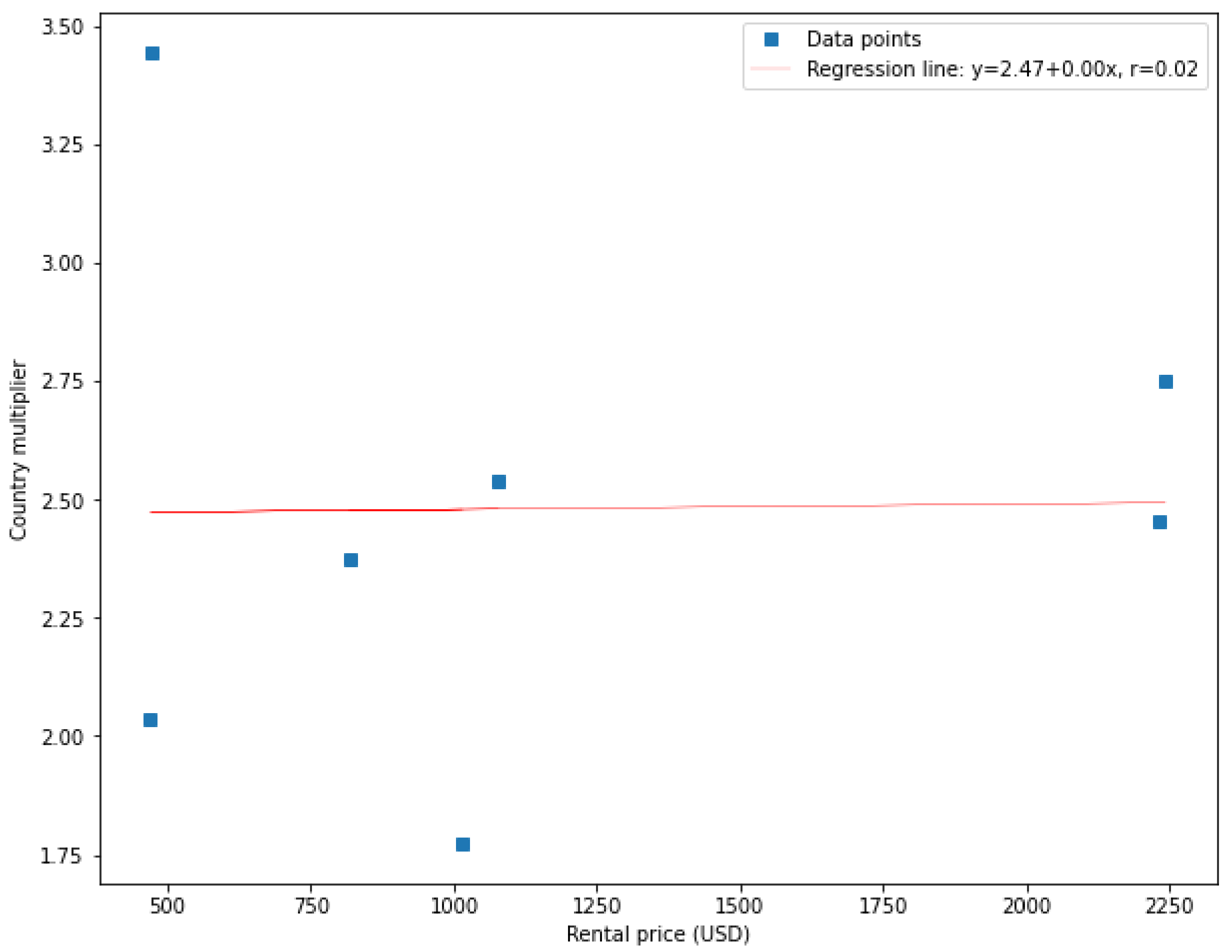
```
Germany : 1077.8536438127092
Guatemala : 468.36725000000007
Morocco : 1015.3
South Korea : 471.7000000000001
UK : 2231.6217
USA : 2242.3847965738755
Vietnam : 817.0993192771085
```

```
rental_prices=np.asarray(rental_prices)
country_mult_means=samples['country_mult'].mean(axis=0)
c_matrix=np.corrcoef(rental_prices,country_mult_means)
c_matrix[0,1]
```

```
0.015983442301487252
```

```
#the correlation coefficient appears to be very small
#code inspired from a page on correlation and linear regression in python https://realpython.com/numpy-scipy-panda
slope, intercept, r, p, stderr = sts.linregress(rental_prices,country_mult_means)
```

```
plt.figure(figsize=(10, 8))
plt.plot(rental_prices,country_mult_means,linewidth=0, marker='s', label='Data points')
plt.plot(rental_prices, intercept + slope * rental_prices, label=f'Regression line: y={intercept:.2f}+{slope:.2f}x
#plt.plot(rental_prices, np.poly1d(np.polyfit(rental_prices, country_mult_means, 1))(rental_prices), color='r', li
plt.legend()
plt.xlabel('Rental price (USD)')
plt.ylabel('Country multiplier')
plt.show()
print("Correlation coefficient: {} with p-value of {}".format(round(c_matrix[0,1],3), round(p,3)))
```




```
Correlation coefficient: 0.016 with p-value of 0.973
```

```
country_mult_means
```

```
array([2.54018833, 2.03723486, 1.77340949, 3.44589443, 2.45259   ,
       2.75081475, 2.37320951])
```

```
rental_prices
```

```
array([1077.85364381,  468.36725   , 1015.3       ,  471.7       ,
       2231.6217    , 2242.38479657,  817.09931928])
```

Based on the graph above, it seems that the datapoint in the upper left corner is driving the regression line to have a smaller slope, that datapoint is South Korea. As we can see South Korea has the largest multiplier, but it has almost the cheapest rent price. South Korea might be an example of a country where rent prices do not correlate with how expensive its groceries are. For the sole purpose of finding out, I want to look at the output of the correlation without the South Korea datapoint.

```
country_mult2=np.delete(country_mult_means,3)
country_mult2
```

```
array([2.54018833, 2.03723486, 1.77340949, 2.45259   , 2.75081475,
       2.37320951])
```

```
rental_prices2=np.delete(rental_prices,3)
rental_prices2
```

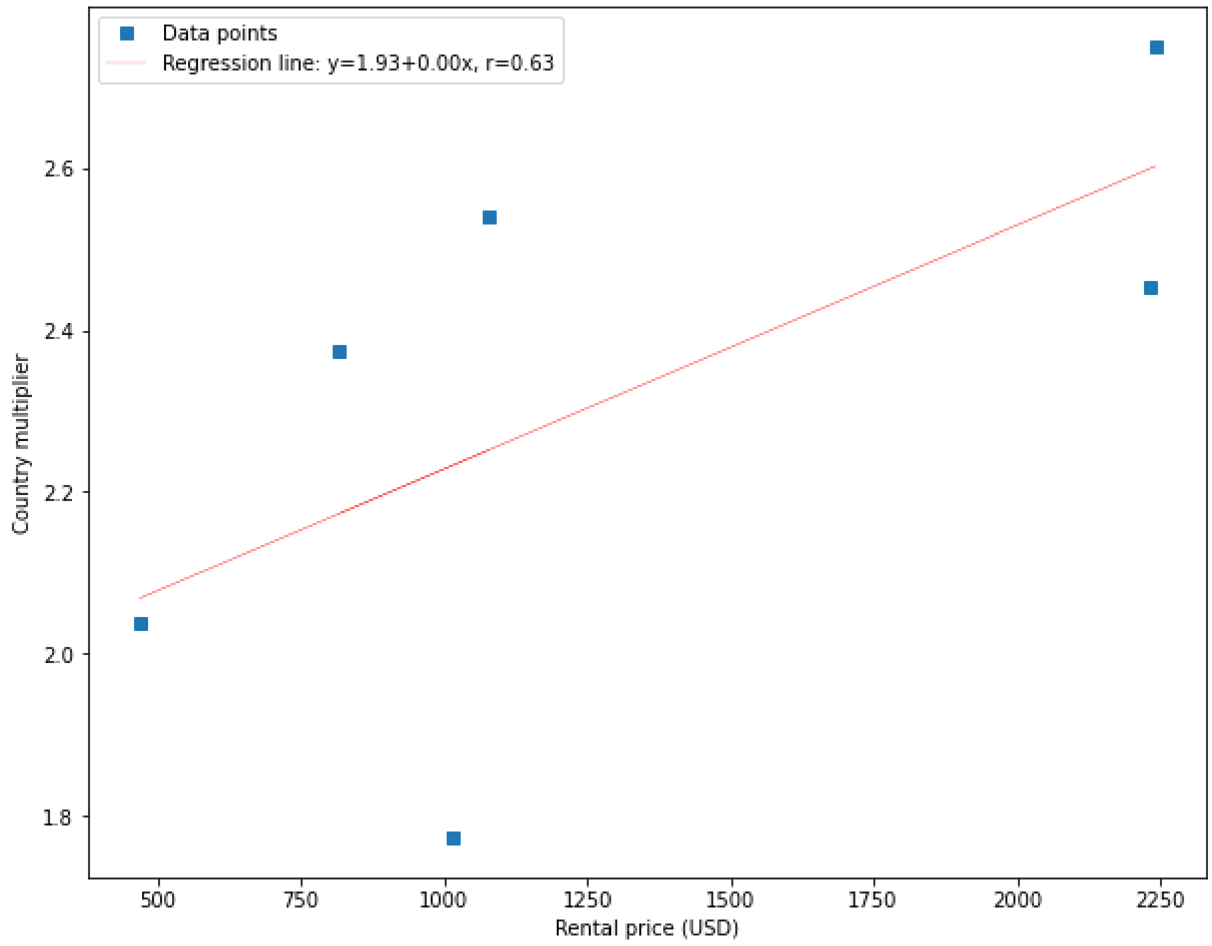
```
array([1077.85364381,  468.36725   , 1015.3       , 2231.6217    ,
       2242.38479657,  817.09931928])
```

```
c_matrix2=np.corrcoef(rental_prices2,country_mult2)
c_matrix2[0,1]
```

```
0.6338533619825264
```

```
slope1, intercept1, r1, p1, stderr1 = sts.linregress(rental_prices2,country_mult2)
```

```
plt.figure(figsize=(10, 8))
plt.plot(rental_prices2,country_mult2,linewidth=0, marker='s', label='Data points')
plt.plot(rental_prices2, intercept1 + slope1 * rental_prices2, label=f'Regression line: y={intercept1:.2f}+{slope1
#plt.plot(rental_prices, np.poly1d(np.polyfit(rental_prices, country_mult_means, 1))(rental_prices), color='r', li
plt.legend()
plt.xlabel('Rental price (USD)')
plt.ylabel('Country multiplier')
plt.show()
print("Correlation coefficient: {} with p-value of {}".format(round(c_matrix2[0,1],3), round(p1,3)))
```




```
Correlation coefficient: 0.634 with p-value of 0.177
```

Without the South Korea datapoint, we have a correlation of 0.6 which is pretty good, however, we still will report the main outcome which is the negative correlation, because while it is true that it correlates for these countries, South Korea is an exception to the rule.