風險管理 作業二

B07607001 鄭鈞瀚

Google Colab 線上版本： Open in Colab

Excel Data: Google Drive Folder

設定亂數種子

```
seed = 0
encode_string = "率慈是我們的偶像，我愛風險管理"

for character in encode_string:
    seed += ord(character)
print(f"Seed: {seed}")
```

```
Seed: 452122
```

Import Third-Party Packages

```
# 移除無用警告
import warnings
warnings.filterwarnings('ignore')

# Pandas: 資料處理用途
import pandas as pd
# Matplotlib: 資料視覺化
import matplotlib.pyplot as plt

plt.rcParams["font.family"] = "sans-serif"
plt.rcParams["font.sans-serif"] = ["Helvetica"]
plt.rcParams["axes.unicode_minus"] = False
plt.style.use("seaborn")

from IPython.display import set_matplotlib_formats

%matplotlib inline
set_matplotlib_formats("svg")

# Sklearn: 迴歸分析, MSE
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
# Seaborn: 資料視覺化
import seaborn as sns
sns.set(rc={'figure.figsize':(11.7,8.27)})
# Numpy: 數學計算, 統計亂數
import numpy as np
# statsmodels: 統計
import statsmodels.api as sm
```

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

Log-normal 轉換

- $\mu = \ln(\frac{m}{\sqrt{1+\frac{v}{m^2}}})$
- $\sigma = \sqrt{\ln(1+\frac{v}{m^2})}$

```
def lognorm_params(mode: float, stddev: float):
    """
    Transform mode and std to lognormal's form

    Args:
        mode(float): 平均數
        stddev(float): 標準差
    Return:
        mu(float): Log-normal 平均數
```

```python
        sigma(float): Log-normal 標準差
    """
    p = np.poly1d([1, -1, 0, 0, -(stddev/mode)**2])
    r = p.roots
    sol = r[(r.imag == 0) & (r.real > 0)].real
    mu = np.log(mode * sol)
    sigma = np.sqrt(np.log(sol))
    return mu, sigma
```

Step 0

資料來源： [USDA ERS - Fruit and Tree Nuts Yearbook Tables]

```python
content_df = pd.read_excel("https://www.ers.usda.gov/webdocs/DataFiles/54499/FruitYearbookCitrusFruit_CTables.xlsx?v=5599.5", sheet_name="Content")
content_df = content_df.rename(columns={"Citrus Fruit: Production, bearing acreage, yield per acre, equivalent-on-tree returns, and juice stock, pack, and movement": "Content"})
content_df
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Content
0	Table C-1--Grapefruit: Bearing acreage and yie...
1	Table C-2--Grapefruit: Production by State, 19...
2	Table C-3--Grapefruit: Utilization of producti...
3	Table C-4--Grapefruit: Equivalent-on-tree retu...
4	Table C-5--All grapefruit: Monthly equivalent-...
5	Table C-6--All grapefruit: Monthly equivalent-...
6	Table C-7--All grapefruit: Monthly equivalent-...
7	Table C-8--All grapefruit: Monthly equivalent-...
8	Table C-9--All grapefruit: Monthly equivalent-...
9	Table C-10--Processed grapefruit: Florida, 198...
10	Table C-11--Frozen concentrated grapefruit jui...
11	Table C-12--Chilled grapefruit juice: Processo...
12	Table C-13--Lemons: Acreage, yield per acre, a...
13	Table C-14--Lemons: Utilization of production,...
14	Table C-15--All lemons: Equivalent-on-tree ret...
15	Table C-16--All lemons: Monthly equivalent-on-...
16	Table C-17--All lemons: Monthly equivalent-on-...
17	Table C-18--All lemons: Monthly equivalent-on-...
18	Table C-19--Oranges: Bearing acreage and yield...
19	Table C-20--Oranges: Production by State, 1980...
20	Table C-21--Oranges: Utilization of production...
21	Table C-22--All oranges: Equivalent-on-tree re...
22	Table C-23--All oranges: Monthly equivalent-on...
23	Table C-24--All oranges: Monthly equivalent on...
24	Table C-25--All oranges: Monthly equivalent on...
25	Table C-26--All oranges: Monthly equivalent on...
26	Table C-27--All oranges: Monthly equivalent on...
27	Table C-28--Processed oranges: Florida, 1980/8...
28	Table C-29--Frozen concentrated orange juice: ...
29	Table C-30--Chilled orange juice: Processors' ...

Question 1

> Background - What are the varieties in Citrus fruit category? What are the primary production states?

資料中共包含 `Grapefruit`, `Lemon` 和 `Orange` 三種作物作物，以下將分項探討

Grapefruit

在 `Grapefruit` 類別中，我們可以觀察到 `Florida` 是最大的生產州，其佔了77.8%的生產比例

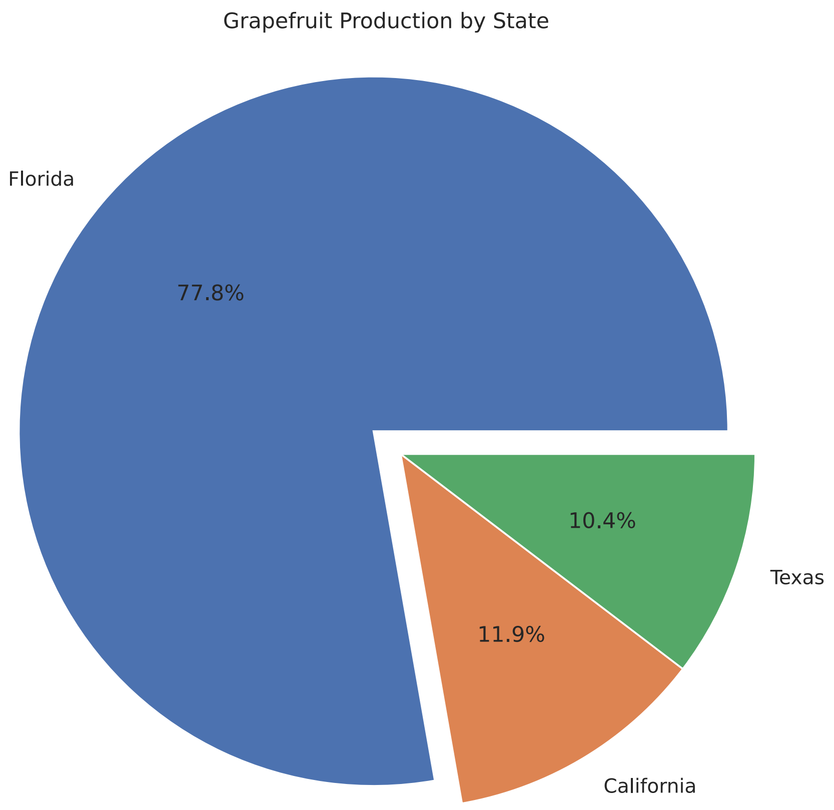
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Production.xlsx", sheet_name="Grapefruit")
df.describe()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Florida	California	Texas	Arizona	United States
count	40.000000	40.000000	38.000000	29.000000	40.000000
mean	1475.393750	225.346875	206.857895	46.333879	1923.963750
std	734.766114	56.410301	99.068482	36.551684	793.000968
min	164.900000	150.750000	2.600000	0.837500	508.900000
25%	815.468750	175.550000	177.500000	5.360000	1224.968750
50%	1738.250000	207.700000	210.000000	46.900000	2174.625000
75%	2108.406250	268.837500	243.000000	77.000000	2610.000000
max	2371.500000	329.750000	556.000000	107.000000	2912.000000

```python
labels = ["Florida", "California", "Texas"]
sizes = [df["Florida"].sum(),
         df["California"].sum(),
         df["Texas"].sum()]
fig1, ax1 = plt.subplots()
separated = (.1,0, 0)
ax1.pie(sizes, labels=labels, autopct="%1.1f%%", explode=separated)
ax1.axis("equal")
plt.title("Grapefruit Production by State")
plt.show()
```



Lemon

在 `Lemon` 類別中，我們可以觀察到僅有 `California` 和 `Arizona` 兩州生產，其中以 `California` 生產較多

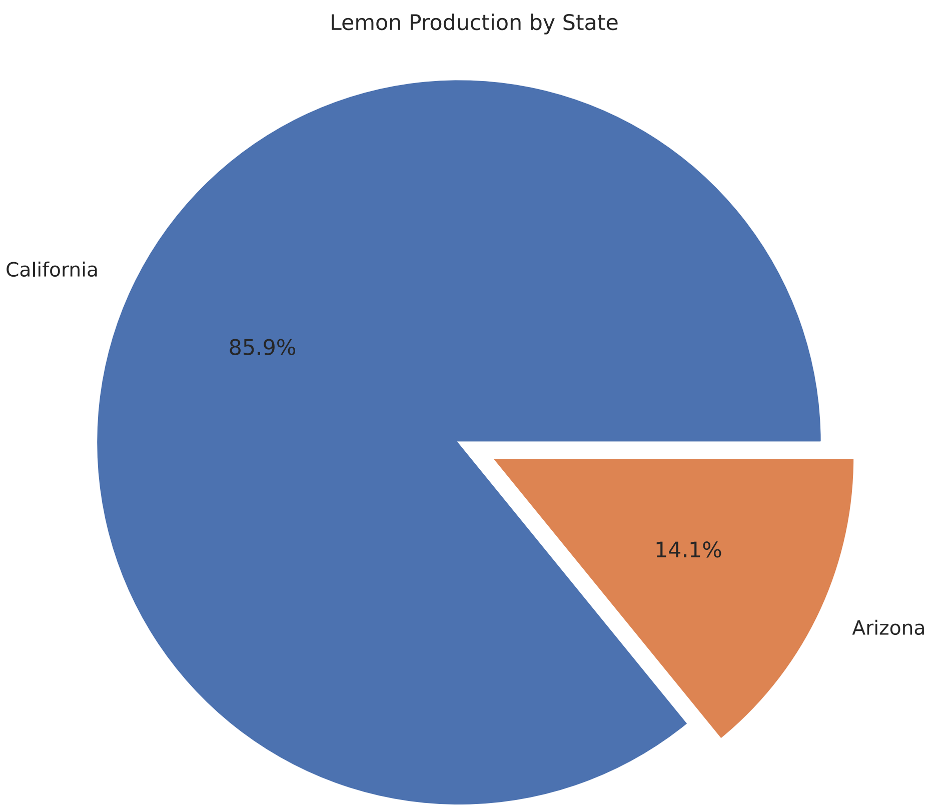
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Production.xlsx", sheet_name="Lemon")
df.describe()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	California	Arizona	United States
count	40.000000	40.000000	40.000000
mean	761.900000	125.200000	887.025000
std	111.416935	58.738971	118.492775
min	562.000000	30.000000	619.000000
25%	692.250000	83.000000	798.000000
50%	783.000000	114.000000	897.000000
75%	827.000000	147.000000	963.250000
max	1028.000000	270.000000	1189.000000

```
labels = ["California", "Arizona"]
sizes = [df["California"].sum(),
         df["Arizona"].sum()]
fig1, ax1 = plt.subplots()
separated = (.1,0)
ax1.pie(sizes, labels=labels, autopct="%1.1f%%", explode=separated)
ax1.axis("equal")
plt.title("Lemon Production by State")
plt.show()
```



Orange

在 `Orange` 類別中，`Florida` 仍為最大生產州，占 75.3% 比例

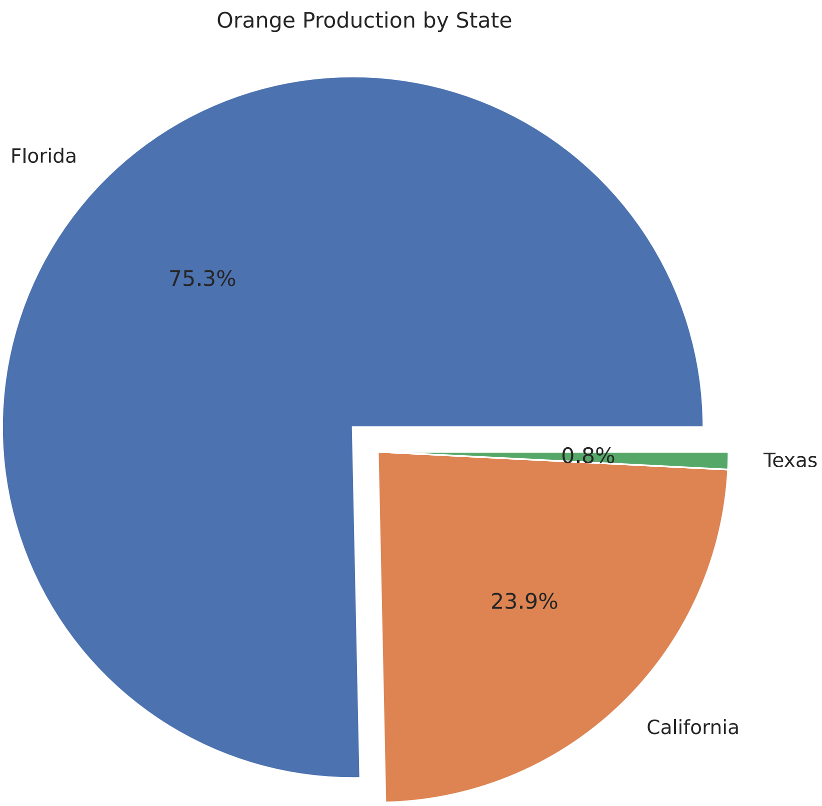
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Production.xlsx", sheet_name="Orange")
df.describe()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Florida	California	Texas	Arizona	United States
count	40.000000	40.000000	38.000000	29.000000	40.000000
mean	6739.762500	2133.965625	75.921184	54.960345	8985.172125
std	2319.255266	362.916848	50.547718	33.809086	2407.400116
min	2027.250000	961.000000	1.275000	9.375000	3875.150000
25%	5336.000000	1931.812500	58.745625	22.100000	7569.337500
50%	6459.750000	2173.500000	68.743750	59.000000	8929.012500
75%	8376.750000	2388.750000	78.332500	71.250000	10613.250000
max	10980.000000	2853.750000	252.450000	142.000000	13670.000000

```python
labels = ["Florida", "California", "Texas"]
sizes = [df["Florida"].sum(),
         df["California"].sum(),
         df["Texas"].sum()]
fig1, ax1 = plt.subplots()
separated = (.1,0, 0)
ax1.pie(sizes, labels=labels, autopct="%1.1f%%", explode=separated)
ax1.axis("equal")
plt.title("Orange Production by State")
plt.show()
```



Question 2

> Derive returns per acre for each Citrus fruit for each state – Pay attention to the footnotes under Tables, you will be able to derive this value. One Annual Summary is in the Folder, which you can use to double check your answer. Next, divide this returns by usage purpose, fresh and processing, by using the data on utilization (Think how you can do it). Run simple regression of returns per acre on years and states. Concisely explain the potential year and state effects on revenues, albeit it's not the farm level.

>> Hint: What do you need to do in cleaning data given prices across years? Because this is the supply-side information, what's the inflation adjustment base for agricultural commodities compared to the common Consumer Price Index? Use 2015 as the base year. Here we assume fresh fruit is dominant in the marketplace, use category rather than single variety as your reference, and match with the starting year in the production information. Locate data on US Bureau of Labor Statistics: https://www.bls.gov. Specify clearly what data you choose to use to COMBINE with the Citrus Fruits production data from Question 1. Argue why we cannot simply draw the data from the same source on ERS, at the Food Prices Outlook section: https://www.ers.usda.gov/data-products/food-price-outlook/

Return per acre

結果請參見 [Excel Data]

Simple Regression

Grapefruit

Import Grapefruit data and adjust data

```python
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Grapefruit")
del df["Dollars / Box"]
del df["PPI (2015 base)"]
del df["Box weight (pounds)"]
del df["Yield per acre (tons)"]
del df["Bearing acre (1000 acre)"]
del df["Total Return"]

# Drop N/A
df=df.dropna()
df.dtypes
```

```
State                object
Year                  int64
Return per acre     float64
dtype: object
```

`State` and `Year` as x input

```python
X = pd.get_dummies(data=df, columns=["State", "Year"], drop_first=True)
del X["Return per acre"]
X
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	State_California	State_Florida	State_Texas	State_United States	Year_1981	Year_1982	Year_1983	Year_1984	Year_1985	Year_1986
0	0	1	0	0	0	0	0	0	0	0
1	0	1	0	0	1	0	0	0	0	0
2	0	1	0	0	0	1	0	0	0	0
3	0	1	0	0	0	0	1	0	0	0
4	0	1	0	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...
195	0	0	0	1	0	0	0	0	0	0
196	0	0	0	1	0	0	0	0	0	0
197	0	0	0	1	0	0	0	0	0	0
198	0	0	0	1	0	0	0	0	0	0
199	0	0	0	1	0	0	0	0	0	0

186 rows × 43 columns

`Return per acre` as y output

```python
Y = df["Return per acre"]
Y
```

```
0      3047.627644
1      1665.700072
2      1284.080973
3      1975.512948
4      2856.280529
          ...
195    3228.826006
196    3019.524219
197    2250.321514
198    2156.769673
199    2734.720986
Name: Return per acre, Length: 186, dtype: float64
```

Subsets

在這裡我們取 80% 作為訓練樣本，20% 作為測試

```
from sklearn.model_selection import train_test_split
# Random state as seed
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=2021)
```

Linear Regression

Model Training

```
model = LinearRegression()
model.fit(X_train, y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

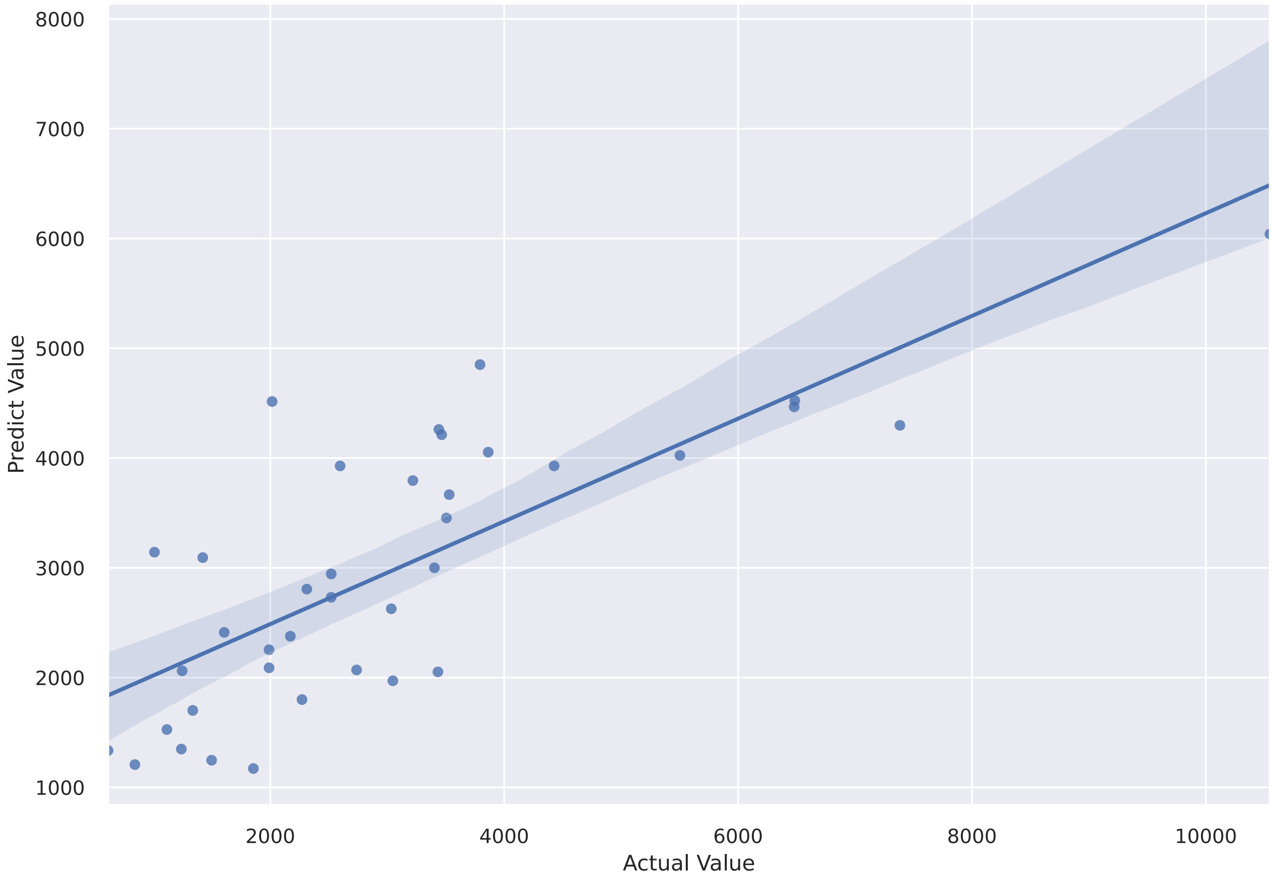
```
print(model.intercept_)
```

```
1267.5086559183246
```

Model Prediction

```
predictions = model.predict(X_test)
ax = sns.regplot(y_test, predictions)
ax.set(xlabel="Actual Value", ylabel="Predict Value")
```

```
[Text(0, 0.5, 'Predict Value'), Text(0.5, 0, 'Actual Value')]
```



Model Summary

```
X_train_Sm= sm.add_constant(X_train)
ls=sm.OLS(y_train,X_train_Sm).fit()
ls.summary()
```

OLS Regression Results

Dep. Variable:	Return per acre	**R-squared:**	0.701
Model:	OLS	**Adj. R-squared:**	0.577
Method:	Least Squares	**F-statistic:**	5.658
Date:	Sat, 05 Jun 2021	**Prob (F-statistic):**	2.78e-13
Time:	05:28:21	**Log-Likelihood:**	-1200.7
No. Observations:	148	**AIC:**	2489.
Df Residuals:	104	**BIC:**	2621.
Df Model:	43		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	1267.5087	581.870	2.178	0.032	113.638	2421.379
State_California	2483.5988	294.748	8.426	0.000	1899.103	3068.094
State_Florida	703.4064	278.897	2.522	0.013	150.344	1256.469
State_Texas	259.5028	285.035	0.910	0.365	-305.732	824.737
State_United States	917.4532	278.897	3.290	0.001	364.391	1470.516
Year_1981	-937.7082	741.102	-1.265	0.209	-2407.342	531.925
Year_1982	-657.8642	741.786	-0.887	0.377	-2128.854	813.126
Year_1983	-568.8666	706.891	-0.805	0.423	-1970.658	832.924
Year_1984	1609.9503	790.810	2.036	0.044	41.744	3178.157
Year_1985	645.8796	706.891	0.914	0.363	-755.911	2047.671
Year_1986	1250.1952	706.891	1.769	0.080	-151.596	2651.986
Year_1987	1278.9353	737.708	1.734	0.086	-183.968	2741.838
Year_1988	81.2096	792.461	0.102	0.919	-1490.270	1652.689
Year_1989	1615.5066	737.708	2.190	0.031	152.603	3078.410
Year_1990	904.0498	737.708	1.225	0.223	-558.853	2366.953
Year_1991	177.1634	741.786	0.239	0.812	-1293.827	1648.153
Year_1992	461.3198	741.786	0.622	0.535	-1009.670	1932.310
Year_1993	98.8177	737.849	0.134	0.894	-1364.365	1562.001
Year_1994	-95.8786	796.498	-0.120	0.904	-1675.363	1483.606
Year_1995	-59.9813	742.522	-0.081	0.936	-1532.430	1412.467
Year_1996	-751.0041	741.786	-1.012	0.314	-2221.994	719.986
Year_1997	46.7989	706.891	0.066	0.947	-1354.992	1448.590
Year_1998	546.6585	795.757	0.687	0.494	-1031.357	2124.674
Year_1999	-84.3096	741.786	-0.114	0.910	-1555.300	1386.680
Year_2000	534.6181	737.708	0.725	0.470	-928.285	1997.521
Year_2001	68.5540	796.498	0.086	0.932	-1510.931	1648.038
Year_2002	440.5185	737.849	0.597	0.552	-1022.665	1903.702
Year_2003	1269.1318	741.102	1.712	0.090	-200.502	2738.765
Year_2004	2289.3526	791.716	2.892	0.005	719.350	3859.355
Year_2005	3247.4979	742.522	4.374	0.000	1775.050	4719.946
Year_2006	715.1553	741.786	0.964	0.337	-755.835	2186.145
Year_2007	433.4555	742.522	0.584	0.561	-1038.993	1905.904
Year_2008	406.1011	792.461	0.512	0.609	-1165.378	1977.581
Year_2009	1131.9168	742.522	1.524	0.130	-340.531	2604.365
Year_2010	1693.2032	742.522	2.280	0.025	220.755	3165.651
Year_2011	1819.9429	742.522	2.451	0.016	347.495	3292.391
Year_2012	1022.6745	742.522	1.377	0.171	-449.774	2495.123
Year_2013	1099.7945	889.682	1.236	0.219	-664.478	2864.067
Year_2014	302.0534	797.207	0.379	0.706	-1278.837	1882.944
Year_2015	1417.4139	792.218	1.789	0.076	-153.584	2988.412
Year_2016	772.2831	797.207	0.969	0.335	-808.608	2353.174
Year_2017	177.6208	797.207	0.223	0.824	-1403.270	1758.512
Year_2018	-32.6156	742.522	-0.044	0.965	-1505.064	1439.833
Year_2019	272.8399	889.682	0.307	0.760	-1491.432	2037.112

Omnibus:	5.047	Durbin-Watson:	1.955
Prob(Omnibus):	0.080	Jarque-Bera (JB):	5.642
Skew:	0.231	Prob(JB):	0.0595
Kurtosis:	3.838	Cond. No.	49.9

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Lemon

Import Lemon data and adjust data

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Lemon")
del df["Dollars / Box"]
del df["PPI (2015 base)"]
del df["Box weight (pounds)"]
del df["Yield per acre (tons)"]
del df["Bearing acre (1000 acre)"]
del df["Total Return"]

# Drop N/A
df=df.dropna()
df.dtypes
```

```
State              object
Year                int64
Return per acre   float64
dtype: object
```

`State` and `Year` as x input

```
X = pd.get_dummies(data=df, columns=["State", "Year"], drop_first=True)
del X["Return per acre"]
X
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	State_California	State_United States	Year_1981	Year_1982	Year_1983	Year_1984	Year_1985	Year_1986	Year_1987	Year_1988	Ye
0	1	0	0	0	0	0	0	0	0	0	0
1	1	0	1	0	0	0	0	0	0	0	0
2	1	0	0	1	0	0	0	0	0	0	0
3	1	0	0	0	1	0	0	0	0	0	0
4	1	0	0	0	0	1	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
112	0	1	0	0	0	0	0	0	0	0	0
116	0	1	0	0	0	0	0	0	0	0	0
117	0	1	0	0	0	0	0	0	0	0	0
118	0	1	0	0	0	0	0	0	0	0	0
119	0	1	0	0	0	0	0	0	0	0	0

111 rows × 38 columns

`Return per acre` as y output

```
Y = df["Return per acre"]
Y
```

```
0      2084.738249
1      1185.511308
2      1018.211630
3      2428.000136
4      3619.092143
           ...
112    6297.650897
116    9791.412146
117    7397.001644
118    6604.572912
119    7552.463230
Name: Return per acre, Length: 111, dtype: float64
```

Subsets

在這裡我們取 80% 作為訓練樣本，20% 作為測試

```
from sklearn.model_selection import train_test_split
# Random state as seed
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=2021)
```

Linear Regression

Model Training

```
model = LinearRegression()
model.fit(X_train,y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

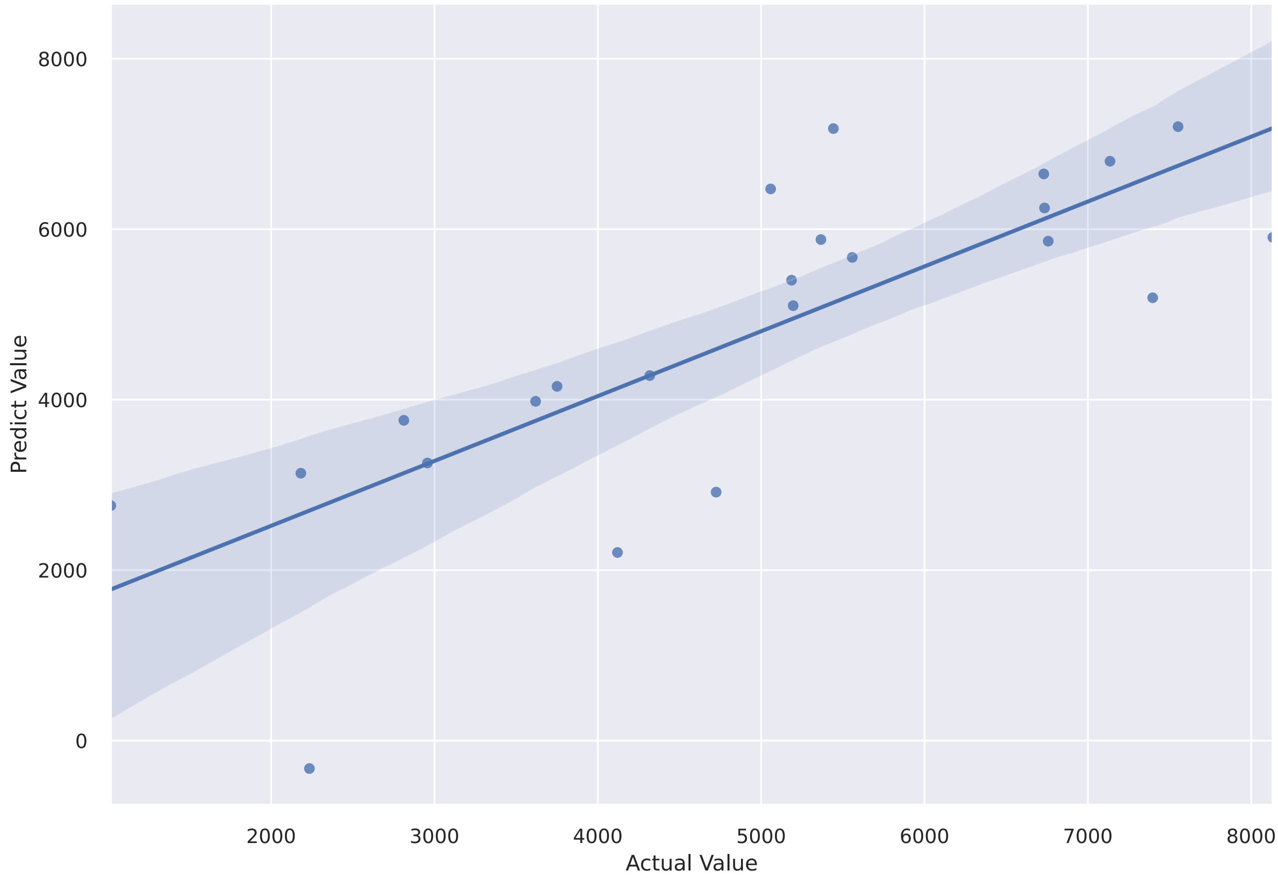
```
print(model.intercept_)
```

```
-327.7689439490923
```

Model Prediction

```
predictions = model.predict(X_test)
ax = sns.regplot(y_test, predictions)
ax.set(xlabel="Actual Value", ylabel="Predict Value")
```

```
[Text(0, 0.5, 'Predict Value'), Text(0.5, 0, 'Actual Value')]
```



Model Summary

```
X_train_Sm= sm.add_constant(X_train)
ls=sm.OLS(y_train,X_train_Sm).fit()
ls.summary()
```

OLS Regression Results

Dep. Variable:	Return per acre	**R-squared:**	0.887
Model:	OLS	**Adj. R-squared:**	0.803
Method:	Least Squares	**F-statistic:**	10.57
Date:	Sat, 05 Jun 2021	**Prob (F-statistic):**	1.20e-13
Time:	05:28:22	**Log-Likelihood:**	-712.68
No. Observations:	88	**AIC:**	1501.
Df Residuals:	50	**BIC:**	1595.
Df Model:	37		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-327.7689	630.870	-0.520	0.606	-1594.909	939.371
State_California	3242.8361	278.904	11.627	0.000	2682.642	3803.030
State_United States	2534.6573	296.352	8.553	0.000	1939.418	3129.897
Year_1981	-817.3184	862.310	-0.948	0.348	-2549.319	914.683
Year_1982	-158.2828	967.808	-0.164	0.871	-2102.183	1785.617
Year_1983	87.0180	862.310	0.101	0.920	-1644.983	1819.019
Year_1984	1065.2830	967.808	1.101	0.276	-878.617	3009.183
Year_1985	2930.0541	862.310	3.398	0.001	1198.053	4662.055
Year_1986	1049.9747	968.240	1.084	0.283	-894.793	2994.743
Year_1987	1949.2068	968.240	2.013	0.049	4.439	3893.975
Year_1988	5.229e-13	2.23e-13	2.342	0.023	7.44e-14	9.71e-13
Year_1989	3462.2852	968.240	3.576	0.001	1517.517	5407.053
Year_1990	3194.7147	968.240	3.300	0.002	1249.947	5139.483
Year_1991	1522.9321	862.310	1.766	0.083	-209.069	3254.933
Year_1992	2968.3672	862.310	3.442	0.001	1236.366	4700.368
Year_1993	4265.6158	1230.189	3.467	0.001	1794.708	6736.524
Year_1994	3582.5887	862.310	4.155	0.000	1850.588	5314.590
Year_1995	3321.3660	862.310	3.852	0.000	1589.365	5053.367
Year_1996	3294.4331	862.310	3.820	0.000	1562.432	5026.434
Year_1997	2485.5077	862.310	2.882	0.006	753.507	4217.509
Year_1998	3671.3004	968.240	3.792	0.000	1726.533	5616.068
Year_1999	2510.8316	862.310	2.912	0.005	778.831	4242.833
Year_2000	2126.1952	862.310	2.466	0.017	394.194	3858.196
Year_2001	3929.7424	862.310	4.557	0.000	2197.741	5661.743
Year_2002	2187.7886	967.808	2.261	0.028	243.888	4131.689
Year_2003	3464.6824	967.484	3.581	0.001	1521.433	5407.931
Year_2004	2075.5030	968.240	2.144	0.037	130.735	4020.271
Year_2005	3652.5280	968.240	3.772	0.000	1707.760	5597.296
Year_2006	4441.7192	968.240	4.587	0.000	2496.951	6386.487
Year_2007	5891.7608	862.310	6.833	0.000	4159.760	7623.762
Year_2008	2229.6196	862.310	2.586	0.013	497.619	3961.621
Year_2009	3476.7224	862.310	4.032	0.000	1744.721	5208.723
Year_2010	3333.7950	967.808	3.445	0.001	1389.895	5277.695
Year_2011	4532.8511	862.310	5.257	0.000	2800.850	6264.852
Year_2012	4085.1993	967.484	4.222	0.000	2141.950	6028.448
Year_2016	6621.8113	862.310	7.679	0.000	4889.810	8353.812
Year_2017	2988.6794	1230.189	2.429	0.019	517.772	5459.587
Year_2018	3882.2676	967.808	4.011	0.000	1938.367	5826.168
Year_2019	4996.1944	968.240	5.160	0.000	3051.426	6940.962

Omnibus:	9.927	**Durbin-Watson:**	1.931
Prob(Omnibus):	0.007	**Jarque-Bera (JB):**	16.922
Skew:	-0.388	**Prob(JB):**	0.000212
Kurtosis:	5.003	**Cond. No.**	2.25e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.15e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Orange

Import Orange data and adjust data

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Orange")
del df["Dollars / Box"]
del df["PPI (2015 base)"]
del df["Box weight (pounds)"]
del df["Yield per acre (tons)"]
del df["Bearing acre (1000 acre)"]
del df["Total Return"]

# Drop N/A
df=df.dropna()
df.dtypes
```

```
State              object
Year                int64
Return per acre   float64
dtype: object
```

`State` and `Year` as x input

```
X = pd.get_dummies(data=df, columns=["State", "Year"], drop_first=True)
del X["Return per acre"]
X
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	State_California	State_Florida	State_Texas	State_United States	Year_1981	Year_1982	Year_1983	Year_1984	Year_1985	Year_1986
0	0	1	0	0	0	0	0	0	0	0
1	0	1	0	0	1	0	0	0	0	0
2	0	1	0	0	0	1	0	0	0	0
3	0	1	0	0	0	0	1	0	0	0
4	0	1	0	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...
195	0	0	0	1	0	0	0	0	0	0
196	0	0	0	1	0	0	0	0	0	0
197	0	0	0	1	0	0	0	0	0	0
198	0	0	0	1	0	0	0	0	0	0
199	0	0	0	1	0	0	0	0	0	0

187 rows × 43 columns

`Return per acre` as y output

```
Y = df["Return per acre"]
Y
```

```
0      2567.386245
1      2035.498171
2      2864.777683
3      3006.075006
4      3587.829189
          ...
195    2728.517987
196    2552.293214
197    2102.370287
198    1765.674552
199    2332.952008
Name: Return per acre, Length: 187, dtype: float64
```

Subsets

在這裡我們取 80% 作為訓練樣本，20% 作為測試

```
from sklearn.model_selection import train_test_split
# Random state as seed
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=2021)
```

Linear Regression

Model Training

```
model = LinearRegression()
model.fit(X_train,y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

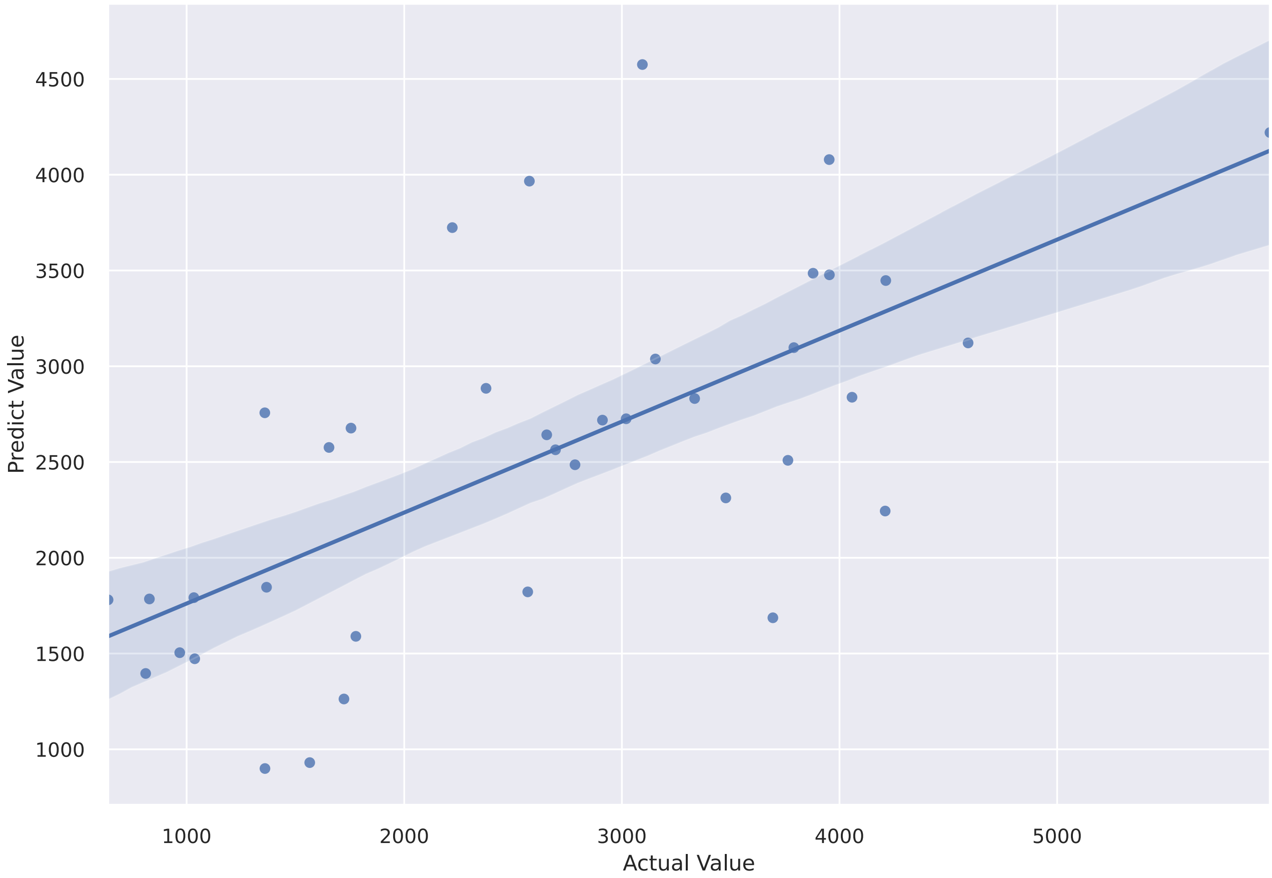
```
print(model.intercept_)
```

```
840.6136643330105
```

Model Prediction

```
predictions = model.predict(X_test)
ax = sns.regplot(y_test, predictions)
ax.set(xlabel="Actual Value", ylabel="Predict Value")
```

```
[Text(0, 0.5, 'Predict Value'), Text(0.5, 0, 'Actual Value')]
```



Model Summary

```
X_train_Sm= sm.add_constant(X_train)
ls=sm.OLS(y_train,X_train_Sm).fit()
ls.summary()
```

OLS Regression Results

Dep. Variable:	Return per acre	**R-squared:**	0.766
Model:	OLS	**Adj. R-squared:**	0.670
Method:	Least Squares	**F-statistic:**	7.979
Date:	Sat, 05 Jun 2021	**Prob (F-statistic):**	2.69e-18
Time:	05:28:23	**Log-Likelihood:**	-1145.1
No. Observations:	149	**AIC:**	2378.
Df Residuals:	105	**BIC:**	2510.
Df Model:	43		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	840.6137	377.445	2.227	0.028	92.210	1589.018
State_California	1966.6375	186.268	10.558	0.000	1597.303	2335.972
State_Florida	981.3090	175.813	5.582	0.000	632.704	1329.914
State_Texas	58.9841	180.015	0.328	0.744	-297.952	415.920
State_United States	1246.0397	175.485	7.101	0.000	898.085	1593.995
Year_1981	798.0564	482.584	1.654	0.101	-158.819	1754.932
Year_1982	916.6288	482.973	1.898	0.060	-41.018	1874.276
Year_1983	808.0932	460.243	1.756	0.082	-104.484	1720.670
Year_1984	1992.3485	514.945	3.869	0.000	971.307	3013.390
Year_1985	289.6803	460.243	0.629	0.530	-622.896	1202.257
Year_1986	940.1767	460.243	2.043	0.044	27.600	1852.753
Year_1987	1676.4033	480.327	3.490	0.001	724.004	2628.802
Year_1988	422.0983	579.238	0.729	0.468	-726.424	1570.620
Year_1989	885.3599	480.327	1.843	0.068	-67.039	1837.759
Year_1990	1204.8794	480.327	2.508	0.014	252.480	2157.279
Year_1991	-130.2433	482.973	-0.270	0.788	-1087.890	827.404
Year_1992	678.2736	482.973	1.404	0.163	-279.373	1635.921
Year_1993	741.9493	480.425	1.544	0.126	-210.644	1694.543
Year_1994	632.0436	518.503	1.219	0.226	-396.052	1660.139
Year_1995	951.1856	518.503	1.834	0.069	-76.910	1979.281
Year_1996	289.9612	482.973	0.600	0.550	-667.686	1247.608
Year_1997	708.5528	460.243	1.540	0.127	-204.024	1621.130
Year_1998	1768.0264	482.973	3.661	0.000	810.379	2725.673
Year_1999	-50.2961	482.973	-0.104	0.917	-1007.943	907.351
Year_2000	880.8208	480.327	1.834	0.070	-71.578	1833.220
Year_2001	555.3257	518.503	1.071	0.287	-472.770	1583.421
Year_2002	-232.1472	480.425	-0.483	0.630	-1184.741	720.446
Year_2003	639.1568	482.584	1.324	0.188	-317.719	1596.032
Year_2004	24.1894	515.502	0.047	0.963	-997.957	1046.336
Year_2005	567.6734	460.243	1.233	0.220	-344.903	1480.250
Year_2006	1159.2493	482.973	2.400	0.018	201.602	2116.896
Year_2007	327.0080	460.243	0.711	0.479	-585.569	1239.585
Year_2008	663.8122	515.771	1.287	0.201	-358.867	1686.491
Year_2009	1112.0453	483.253	2.301	0.023	153.845	2070.246
Year_2010	1396.2496	483.253	2.889	0.005	438.049	2354.450
Year_2011	2220.3259	483.253	4.595	0.000	1262.125	3178.526
Year_2012	1484.2826	483.253	3.071	0.003	526.082	2442.483
Year_2013	1412.9645	579.142	2.440	0.016	264.633	2561.296
Year_2014	670.1000	518.868	1.291	0.199	-358.719	1698.919
Year_2015	787.0836	515.610	1.527	0.130	-235.276	1809.443
Year_2016	640.2859	518.868	1.234	0.220	-388.534	1669.105
Year_2017	314.4778	518.868	0.606	0.546	-714.342	1343.297
Year_2018	-96.6592	483.253	-0.200	0.842	-1054.860	861.541
Year_2019	30.8907	579.142	0.053	0.958	-1117.441	1179.222

Omnibus:	29.863	**Durbin-Watson:**	1.834
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	75.995
Skew:	0.790	**Prob(JB):**	3.15e-17
Kurtosis:	6.121	**Cond. No.**	49.9

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Question 3

> Derive utility levels for each Citrus fruit in each producing State, including US as a whole, using functions exhibiting CARA (one function) and CRRA (two functions). First to derive utilities, what might be the first assumption here given the available data at hand? For the CARA function, assume absolute risk aversion coefficient is 0.003, 0.001, 0.005. For CRRA function, assume r=0.1, 0.5, 0.9 for the function with a non-deterministic value for risk aversion coefficient. Use command twoway to compare utilities across different risk aversion levels under same function, and explain the graph if it makes sense. Under what production technologies, can we examine the utility levels with different levels of risk aversion? If functions represent production techniques, can we compare different technologies for the same fruit in one state or across states?

First assumption

因原本 `CARA` 和 `CRRA` 函式中的 `w` 是指 wealth, 我們並沒有wealth的資料，只能使用 income 代替

CARA Utility

Negative exponential: $U = 1 − exp(−cw), c > 0$

Grapefruit

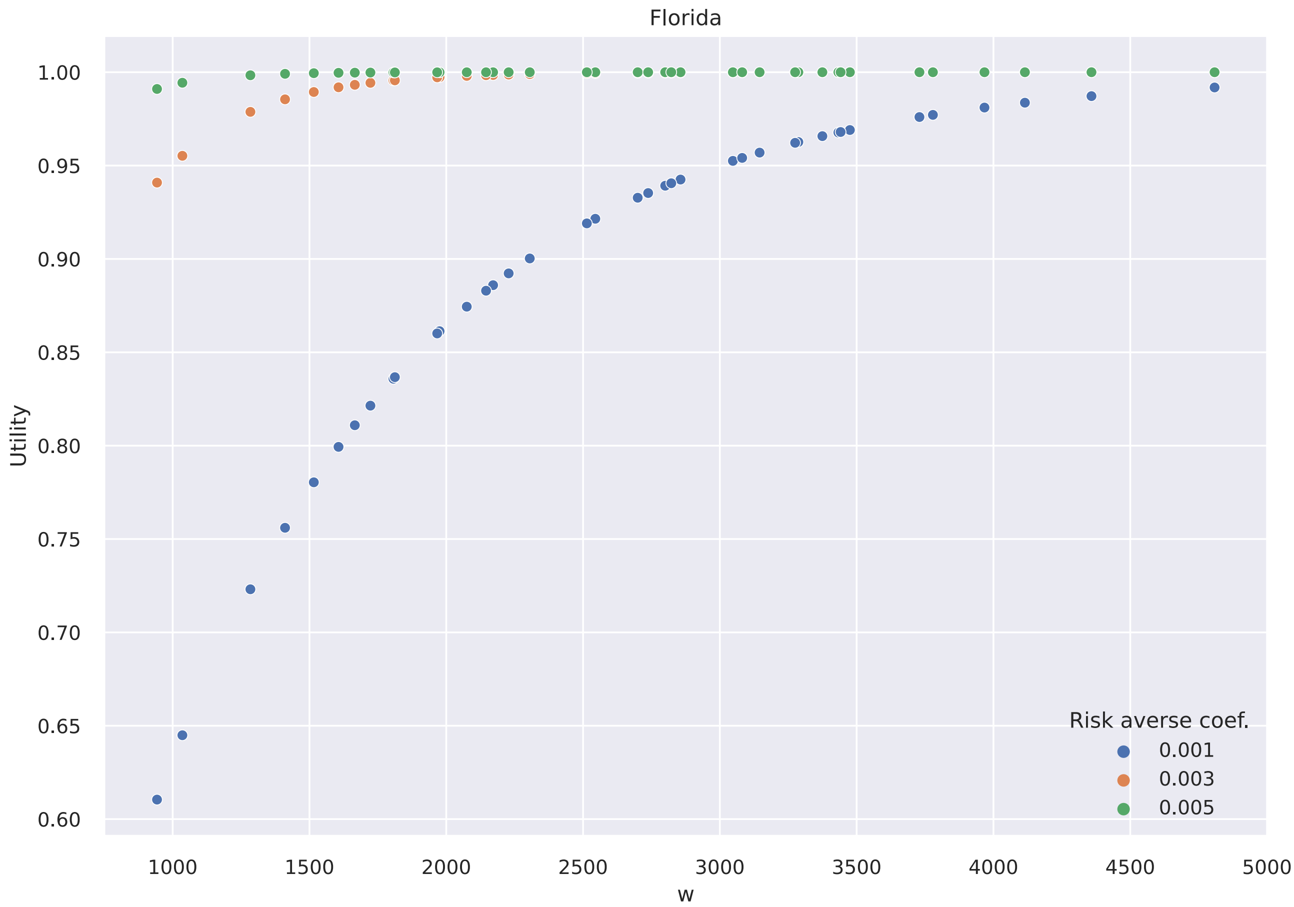
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Grapefruit")
```

Florida

```
sub_df = df[df["State"] == "Florida"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Florida')
```

```
Text(0.5, 1.0, 'Florida')
```

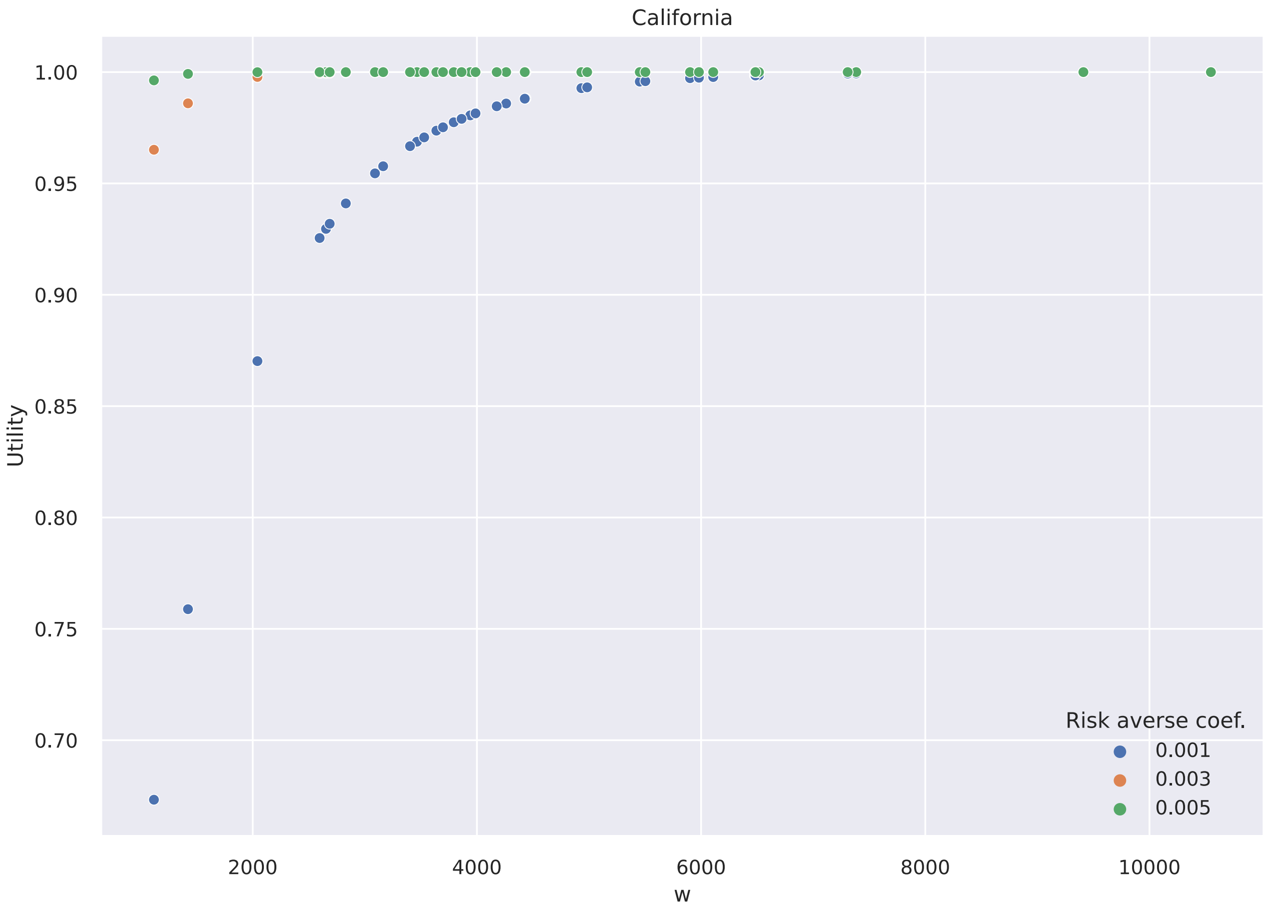


California

```
sub_df = df[df["State"] == "California"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

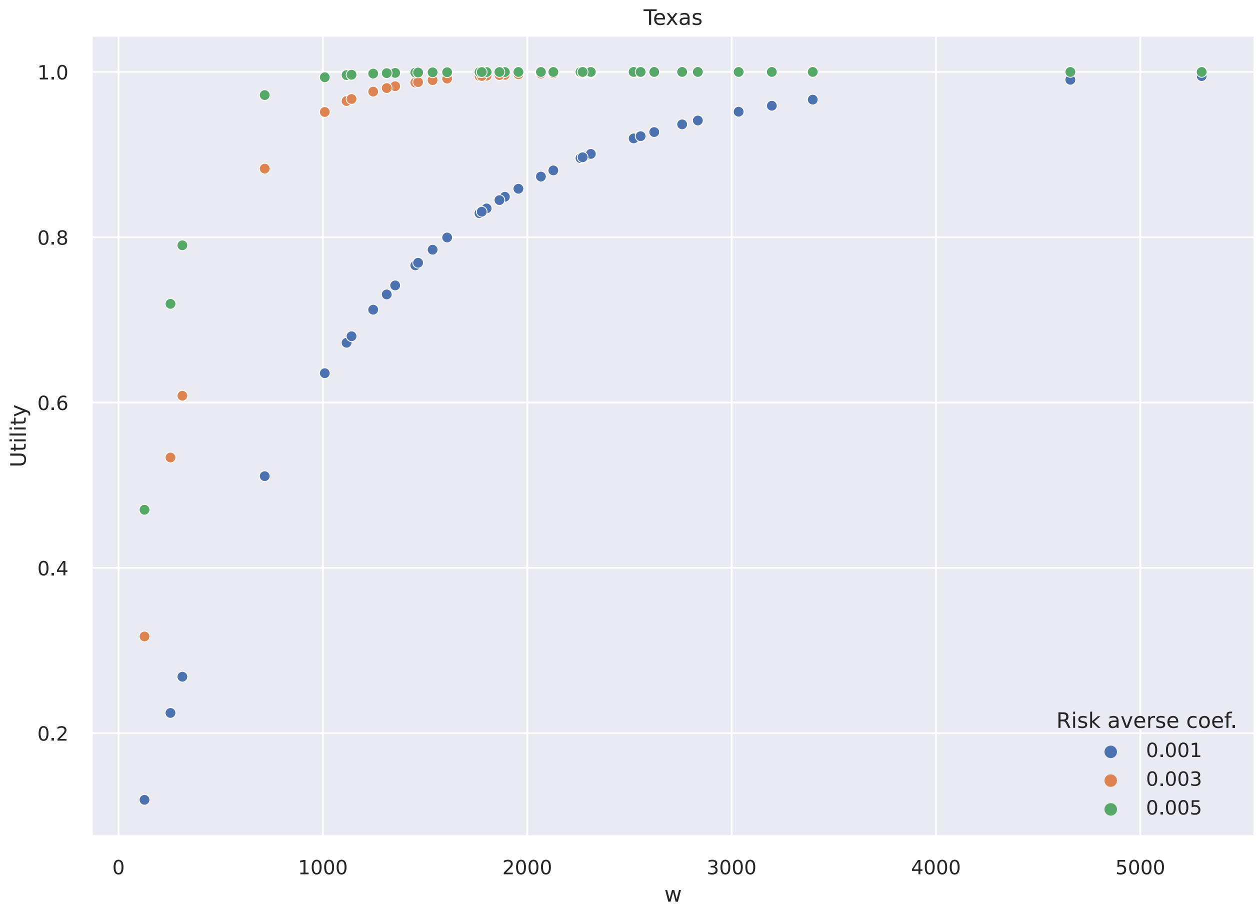


Texas

```
sub_df = df[df["State"] == "Texas"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Texas')
```

```
Text(0.5, 1.0, 'Texas')
```

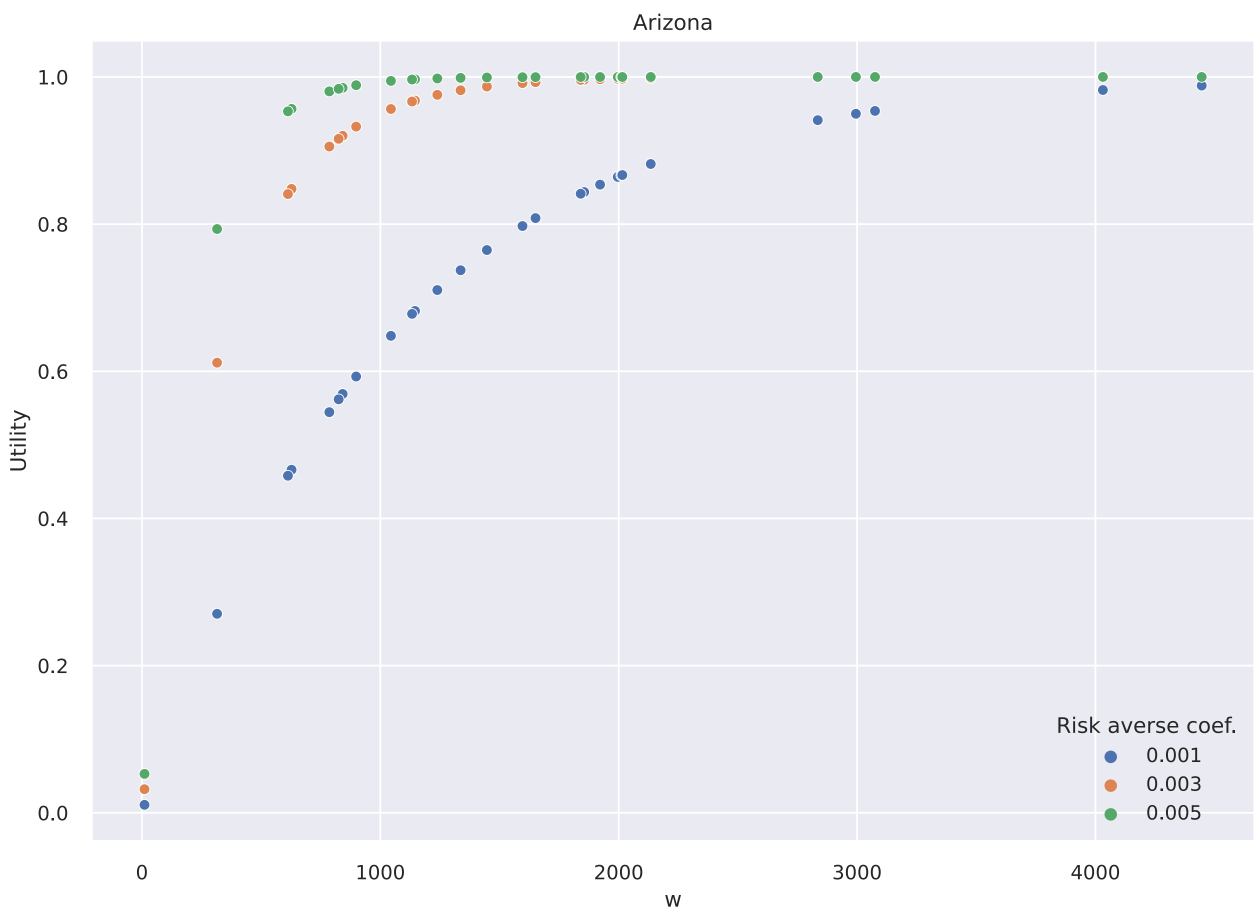


Arizona

```
sub_df = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

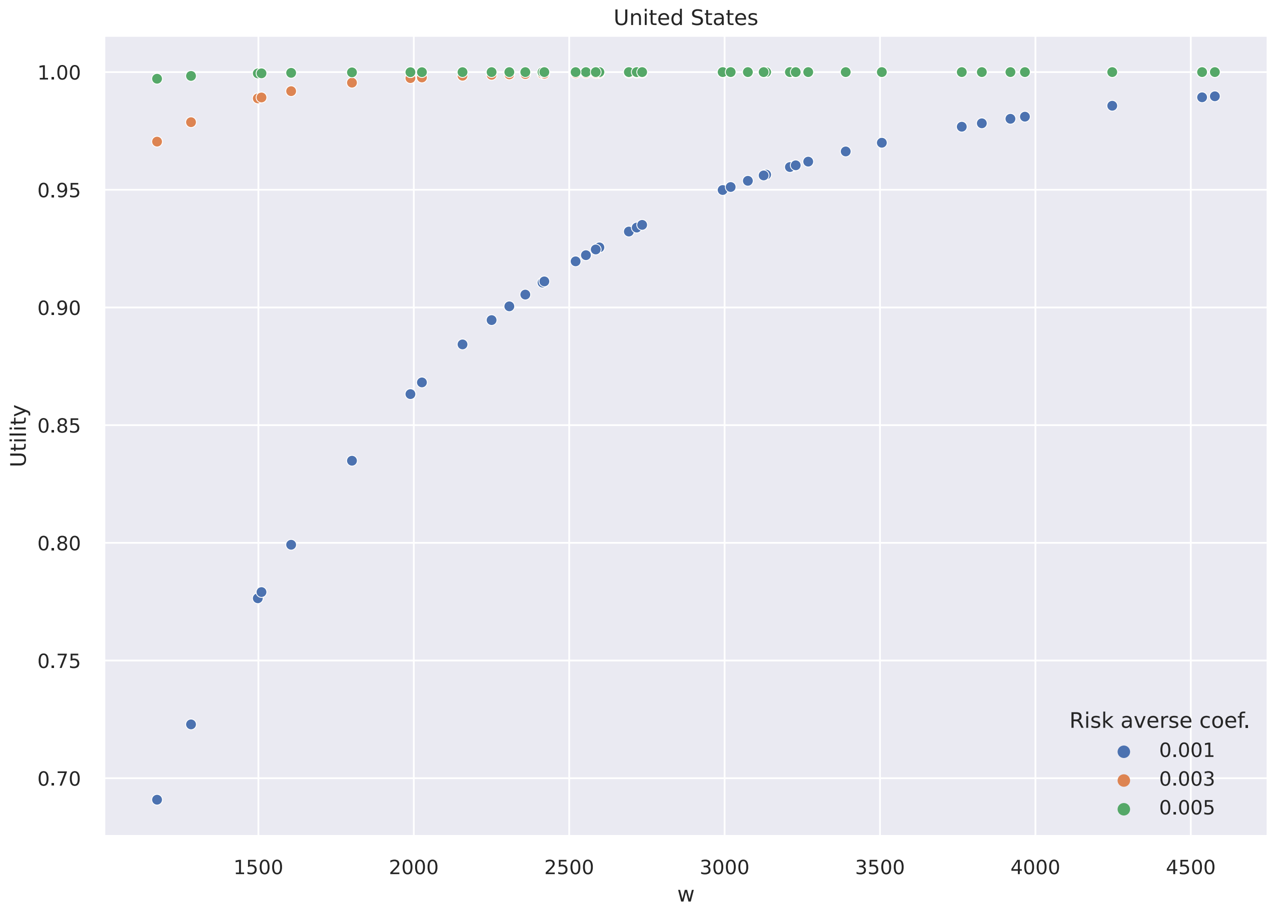


United States

```
sub_df = df[df["State"] == "United States"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Lemon

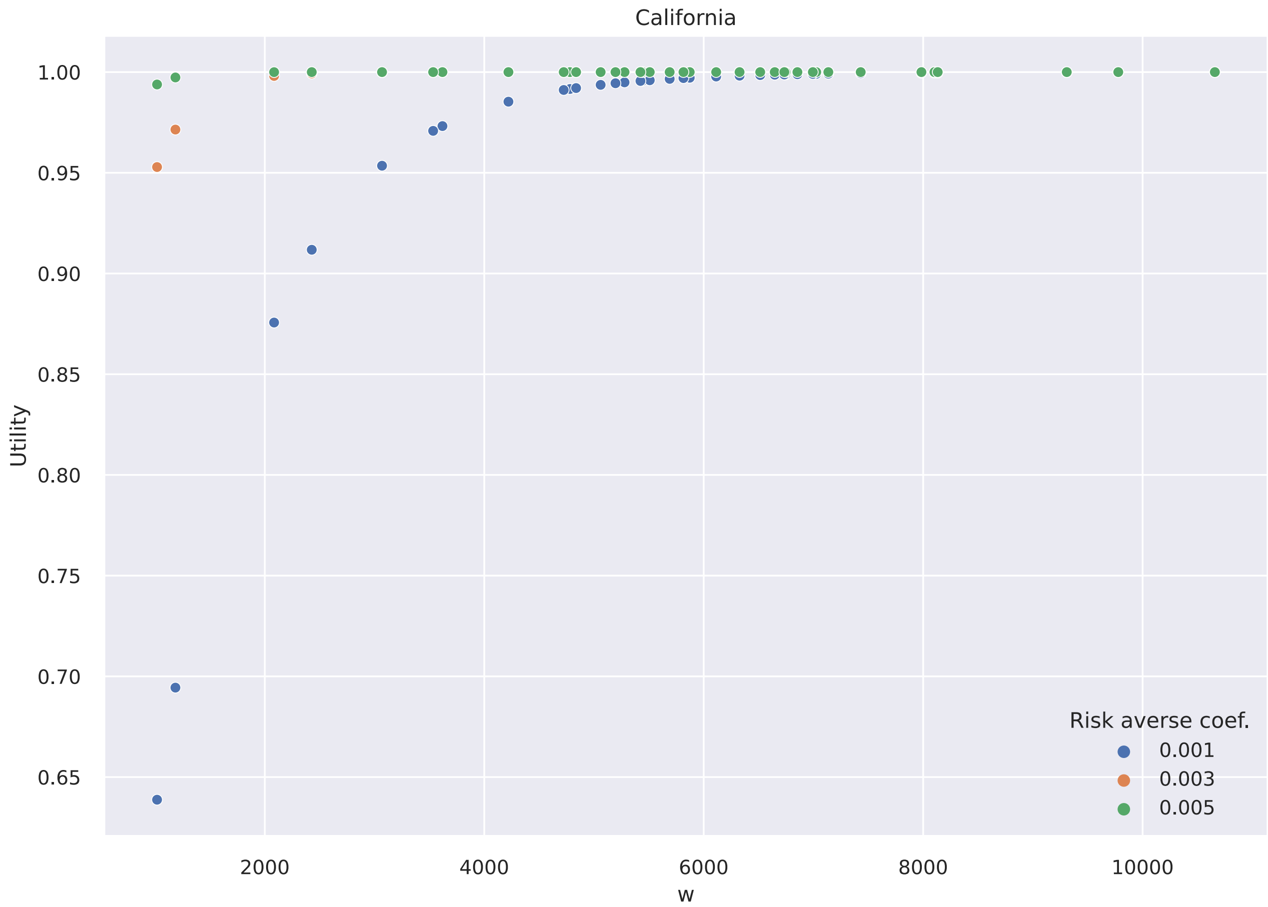
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Lemon")
```

California

```
sub_df = df[df["State"] == "California"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```



Arizona

```python
sub_df = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```python
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Arizona')
```

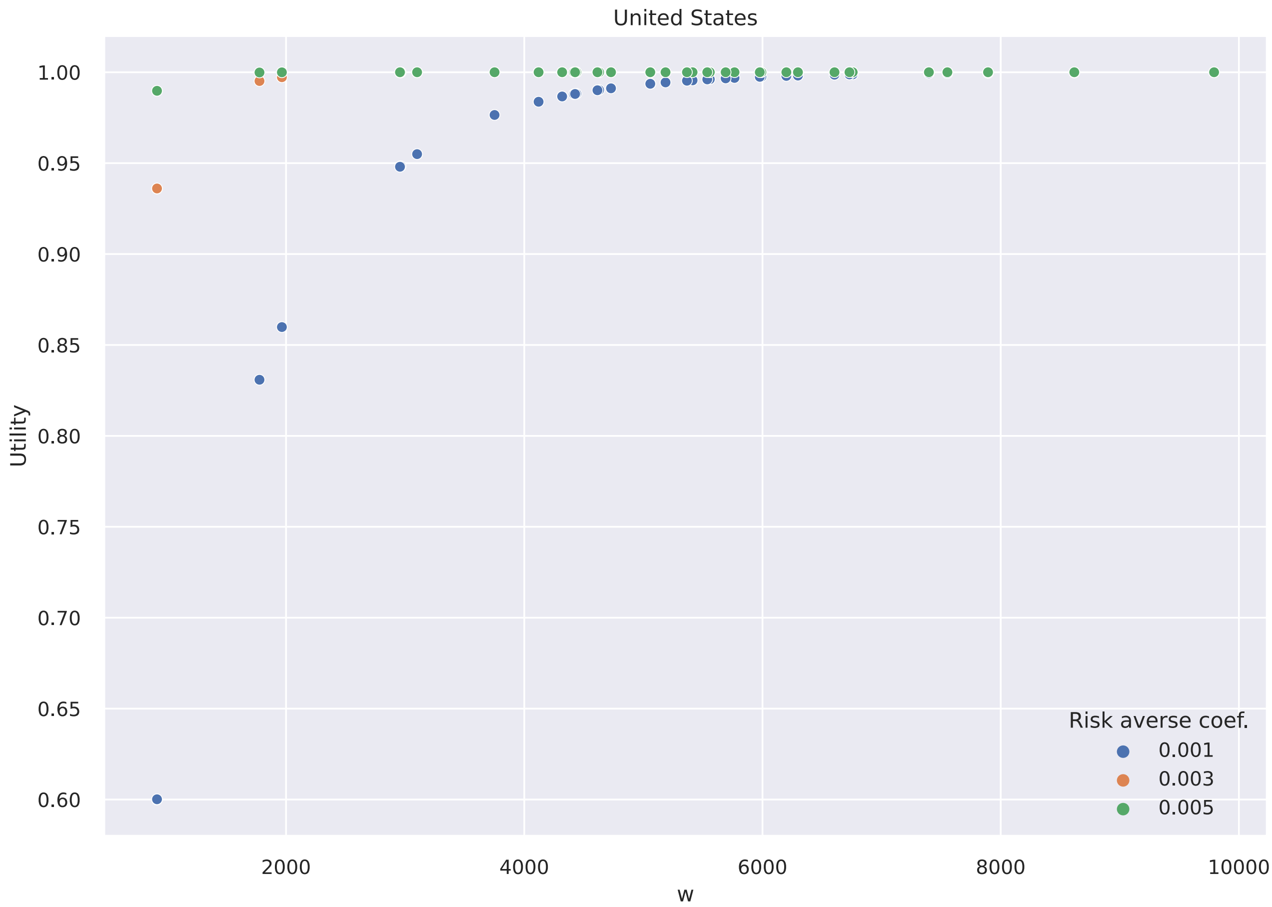
```
Text(0.5, 1.0, 'Arizona')
```

United States

```python
sub_df = df[df["State"] == "United States"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```python
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Orange

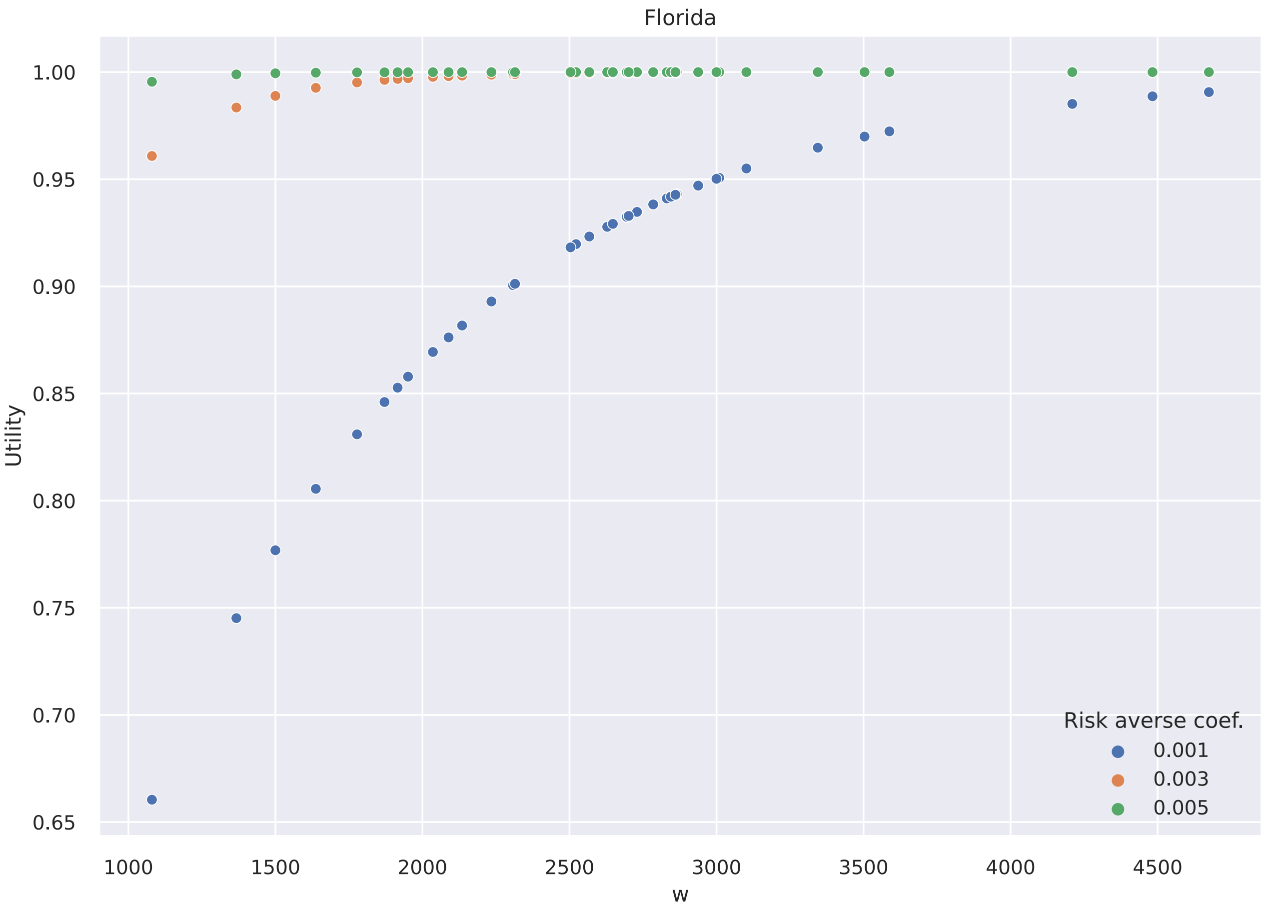
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Orange")
```

Florida

```
sub_df = df[df["State"] == "Florida"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Florida')
```

```
Text(0.5, 1.0, 'Florida')
```



California

```
sub_df = df[df["State"] == "California"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('California')
```

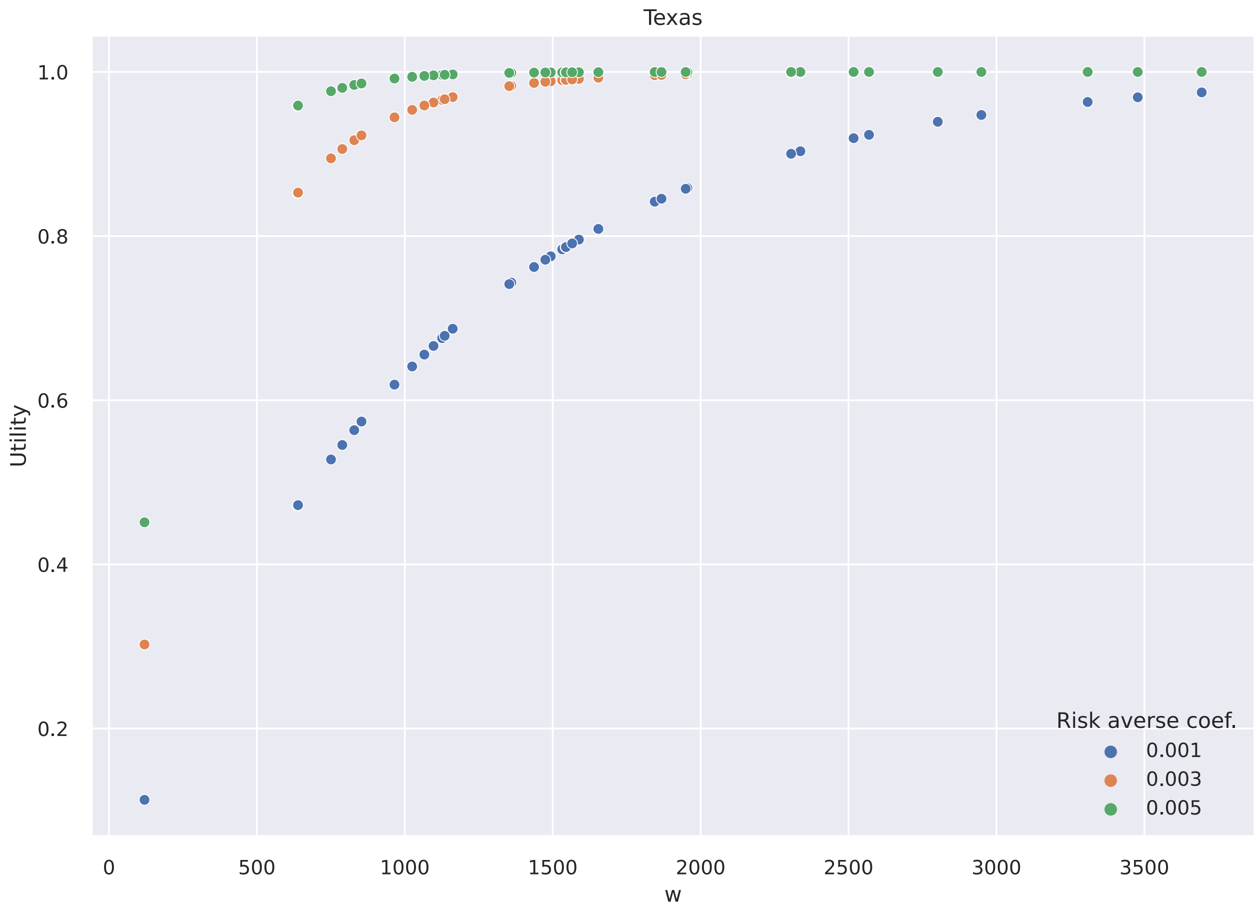
```
Text(0.5, 1.0, 'California')
```

Texas

```
sub_df = df[df["State"] == "Texas"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Texas')
```

```
Text(0.5, 1.0, 'Texas')
```

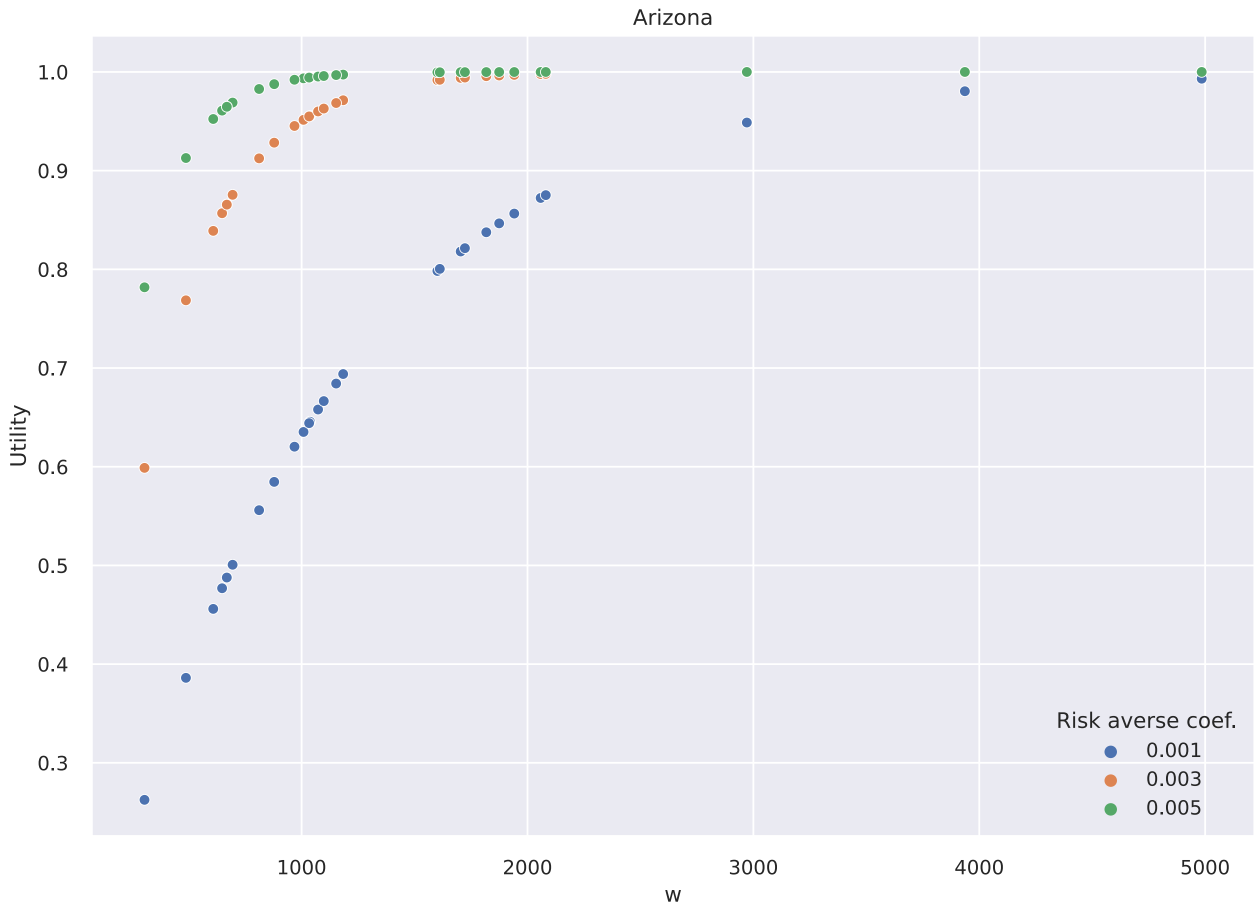


Arizona

```
sub_df = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

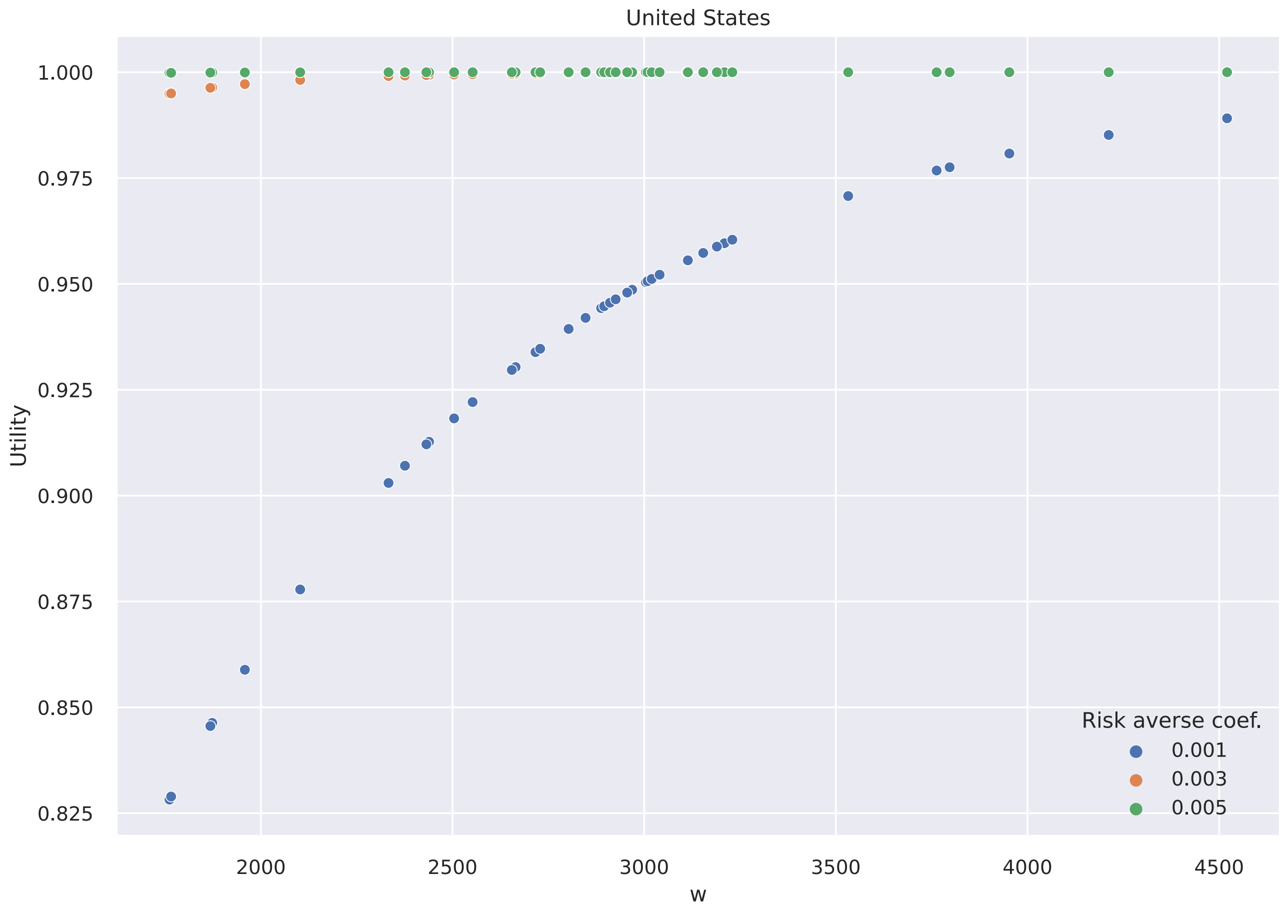


United States

```
sub_df = df[df["State"] == "United States"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# c: 0.003
temp_utility = 1 - np.exp(-0.003 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.003})
plot_df = plot_df.append(temp)
# c: 0.001
temp_utility = 1 - np.exp(-0.001 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.001})
plot_df = plot_df.append(temp)
# c - 0.005
temp_utility = 1 - np.exp(-0.005 * sub_df["Return per acre"])
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.005})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



CRRA Utility - Logarithmic

- Logarithmic: $U = ln(w), w > 0$

  for which $r_{a}(w) = w^{-1}$ and $r_{r}(w) = 1.0$.

Grapefruit

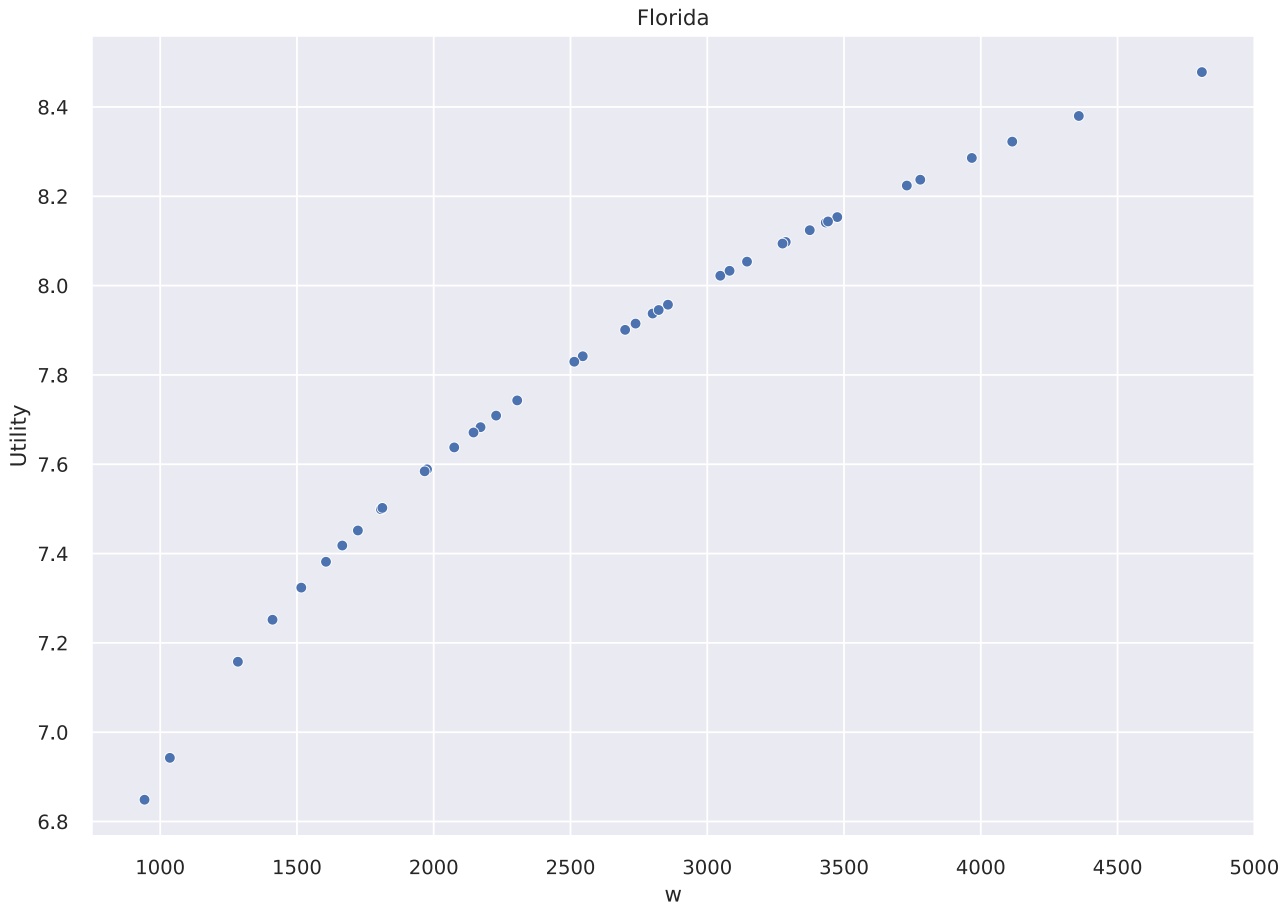
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Grapefruit")
```

Florida

```
temp = df[df["State"] == "Florida"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Florida')
```

```
Text(0.5, 1.0, 'Florida')
```

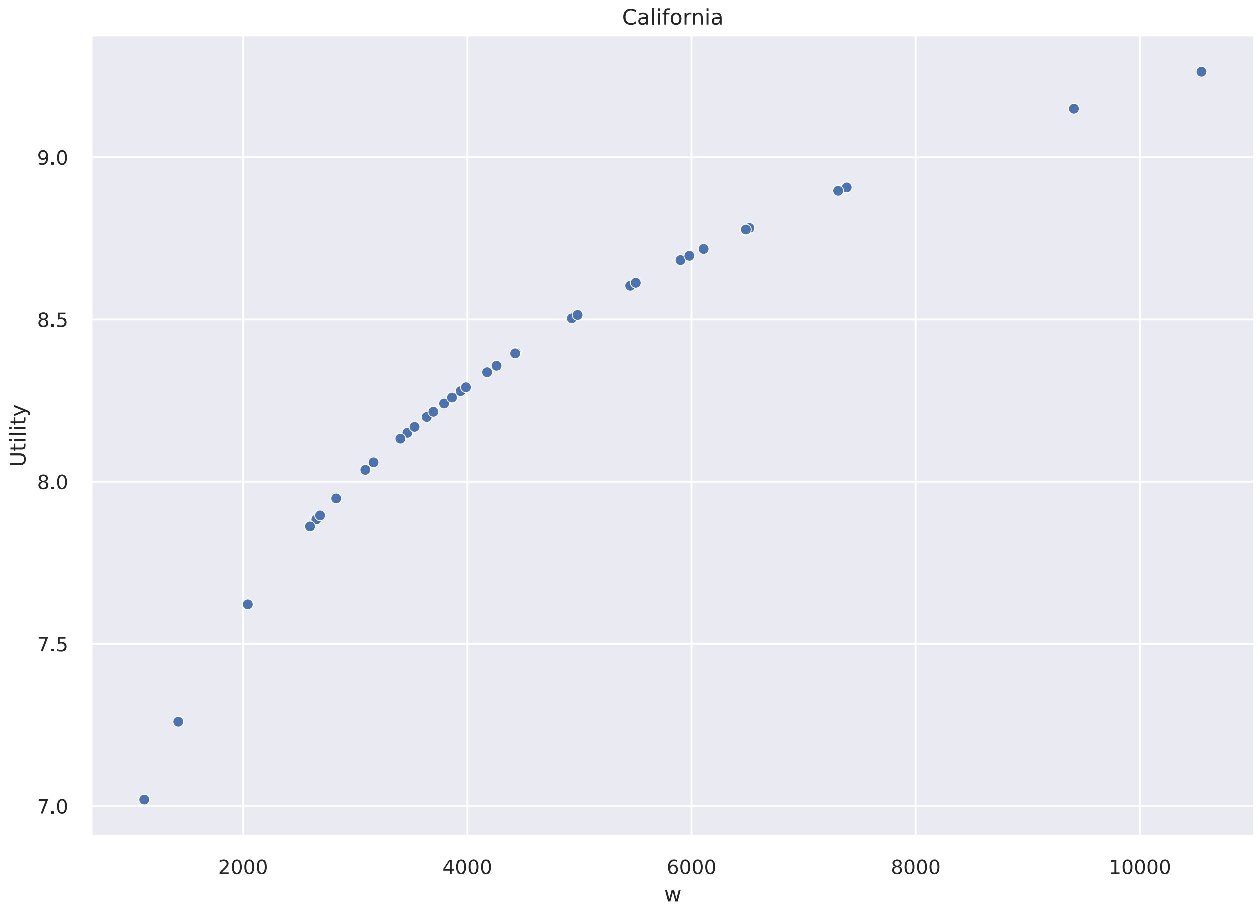


California

```
temp = df[df["State"] == "California"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

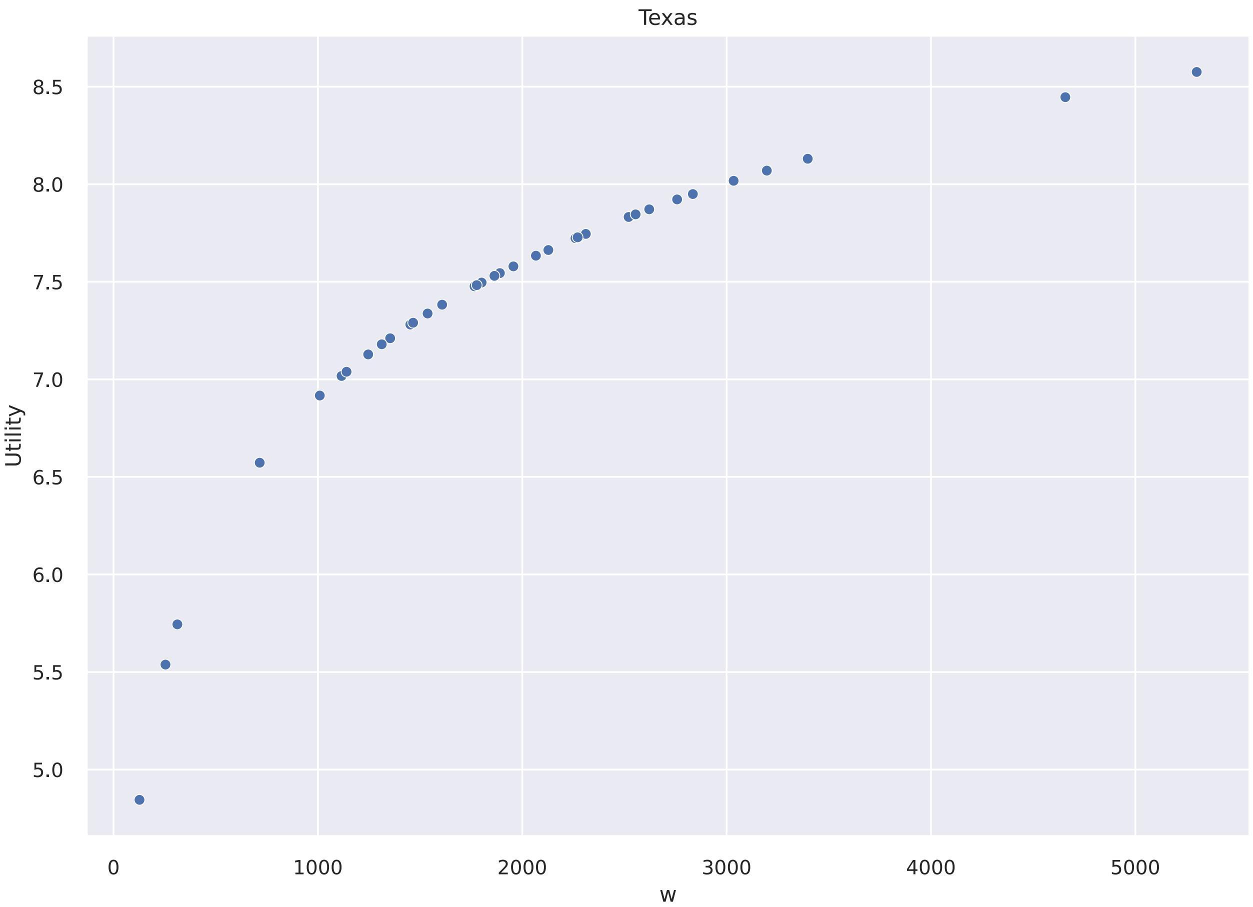


Texas

```
temp = df[df["State"] == "Texas"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Texas')
```

```
Text(0.5, 1.0, 'Texas')
```

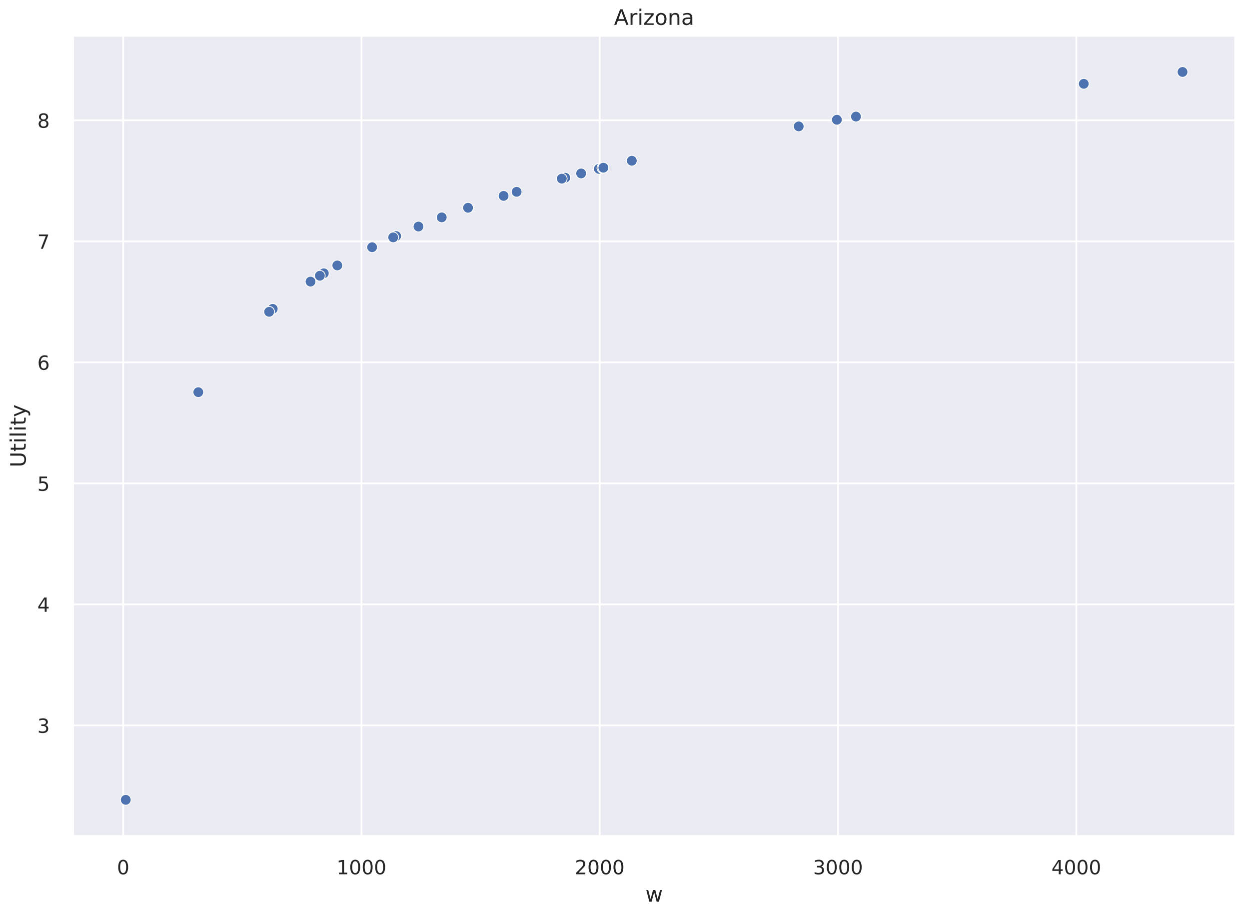


Arizona

```
temp = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

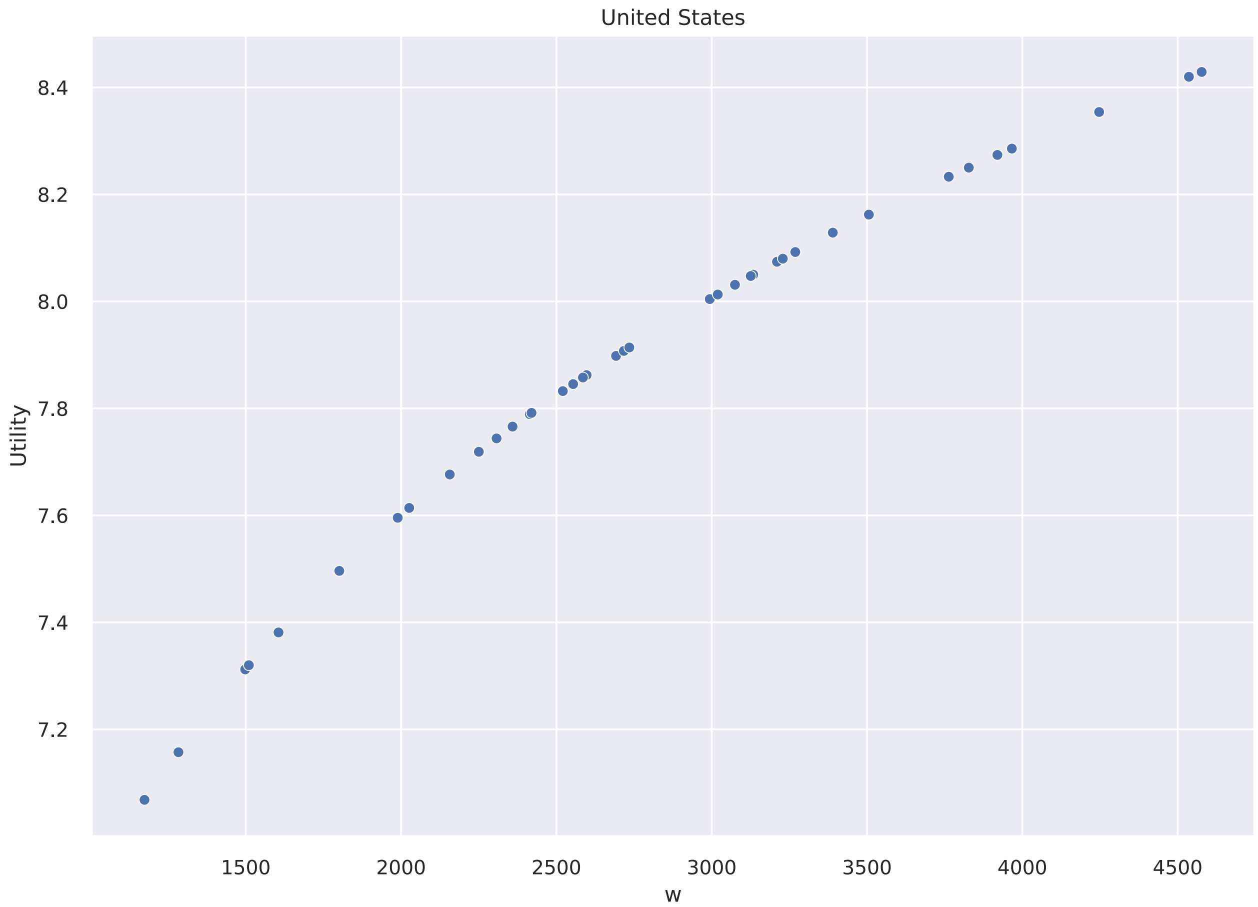


United States

```
temp = df[df["State"] == "United States"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Lemon

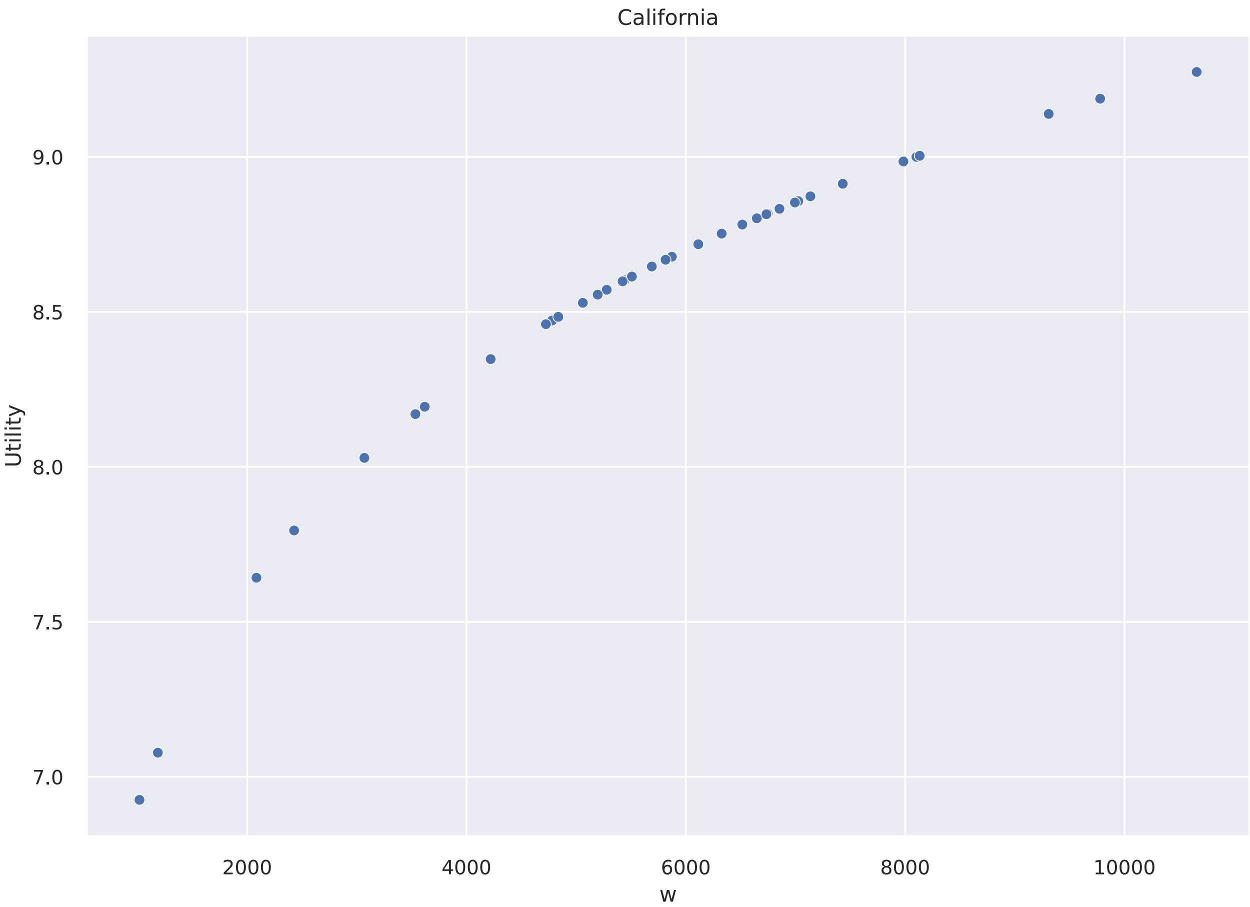
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Lemon")
```

California

```
temp = df[df["State"] == "California"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

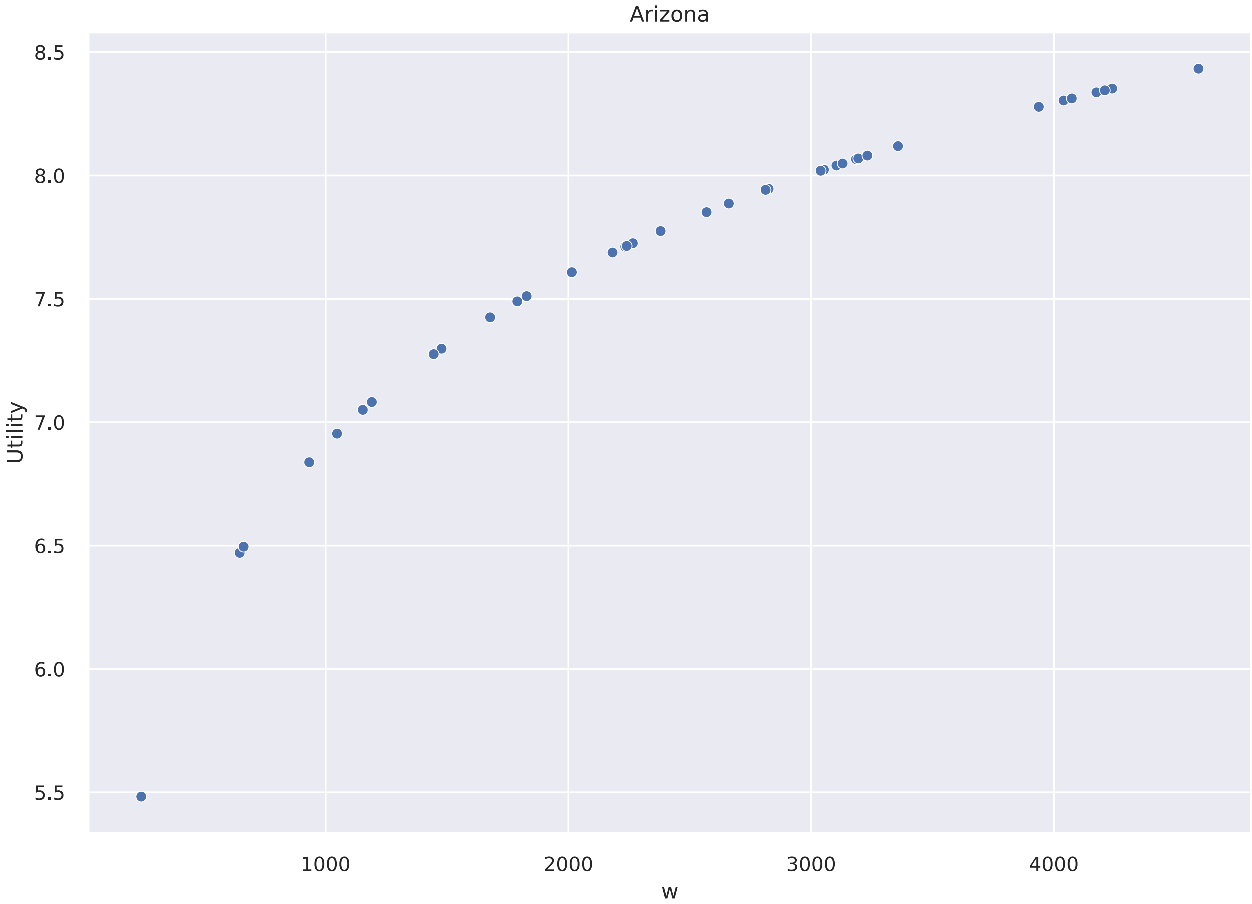


Arizona

```
temp = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

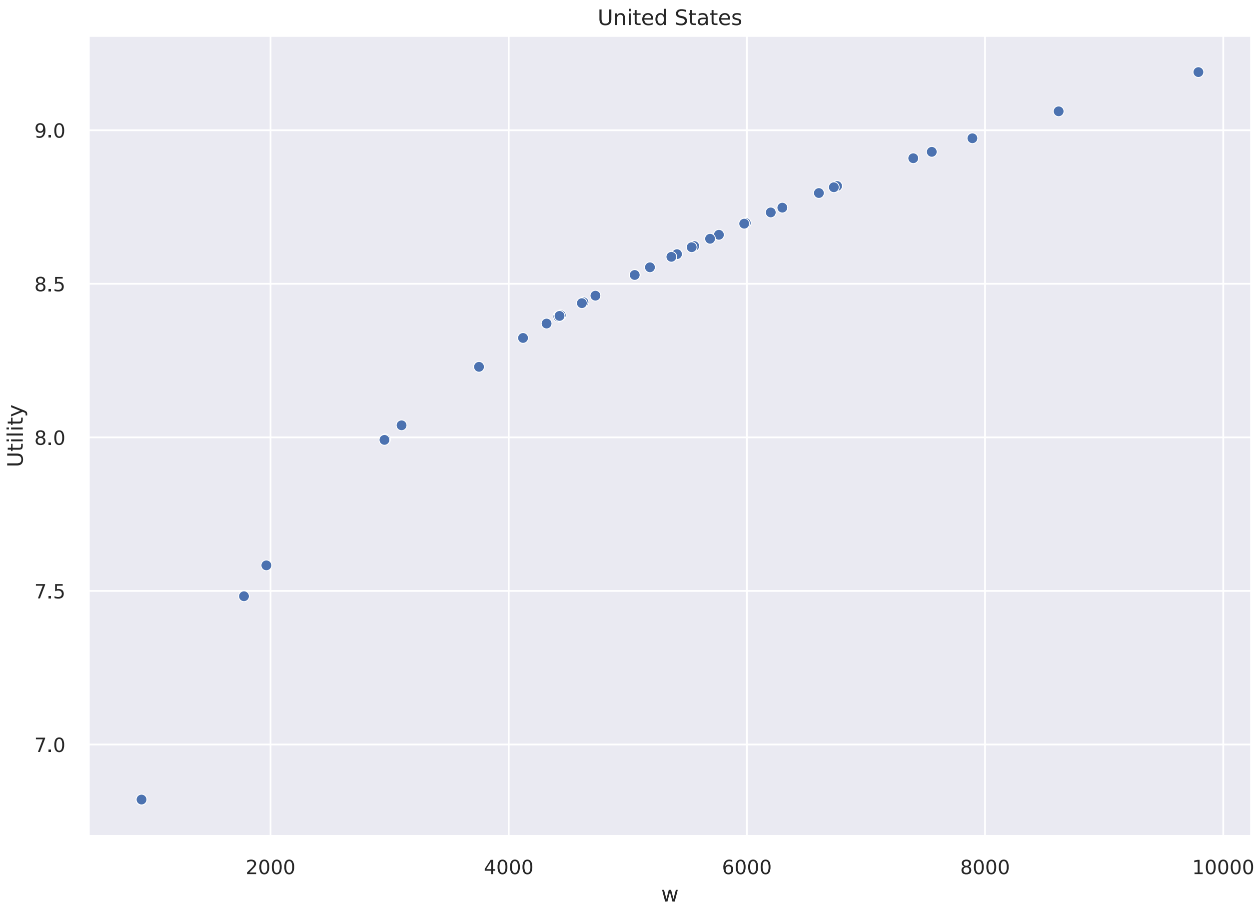


United States

```
temp = df[df["State"] == "United States"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Orange

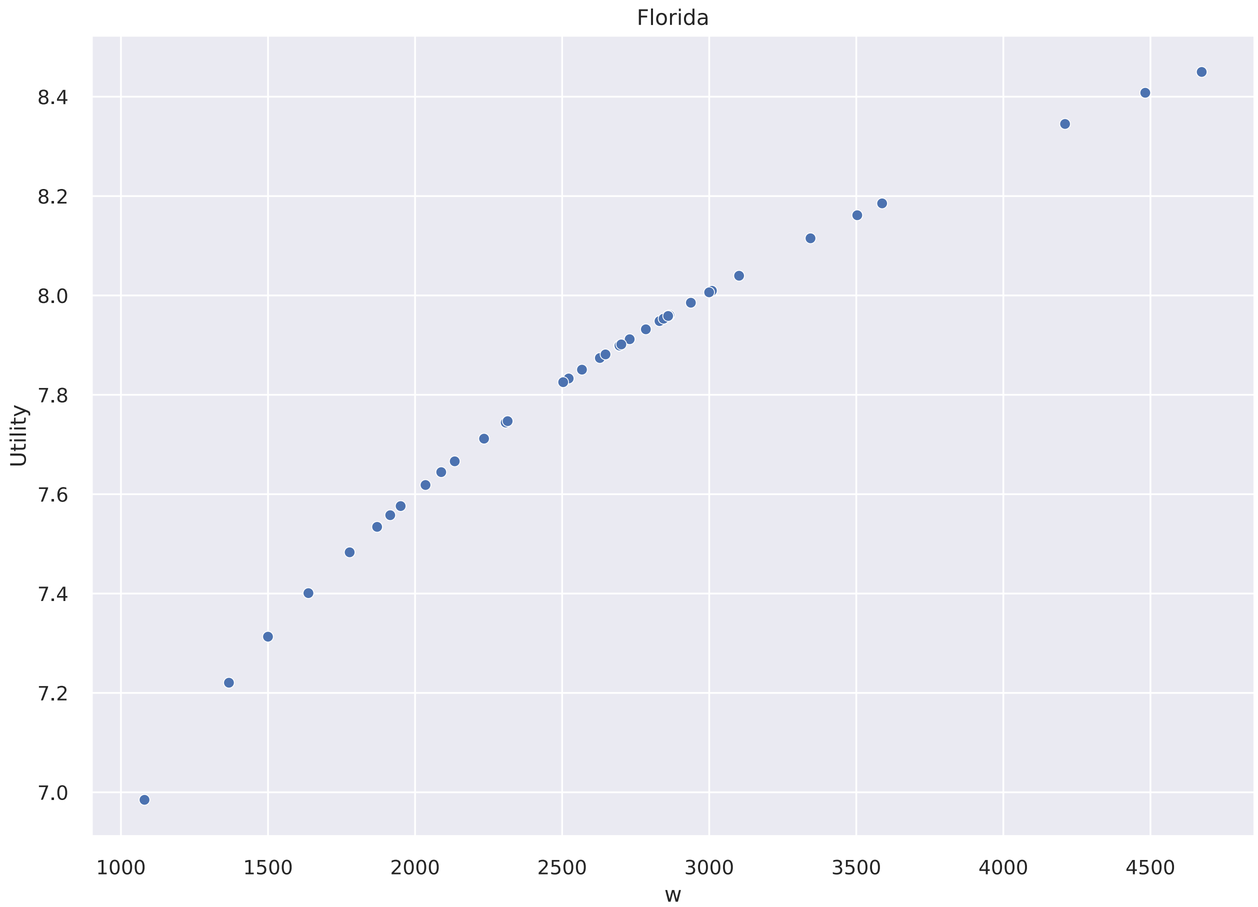
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Orange")
```

Florida

```
temp = df[df["State"] == "Florida"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Florida')
```

```
Text(0.5, 1.0, 'Florida')
```

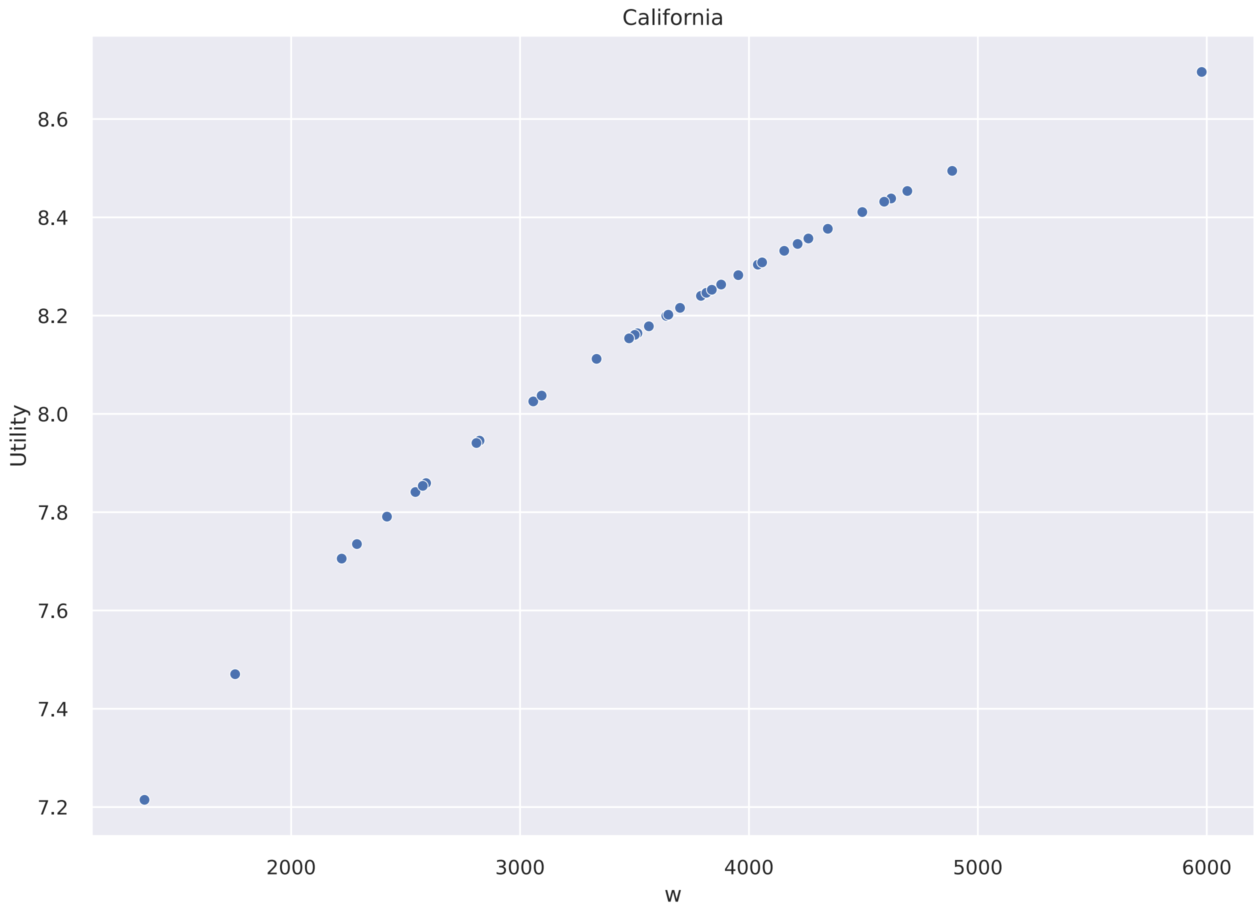


California

```
temp = df[df["State"] == "California"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

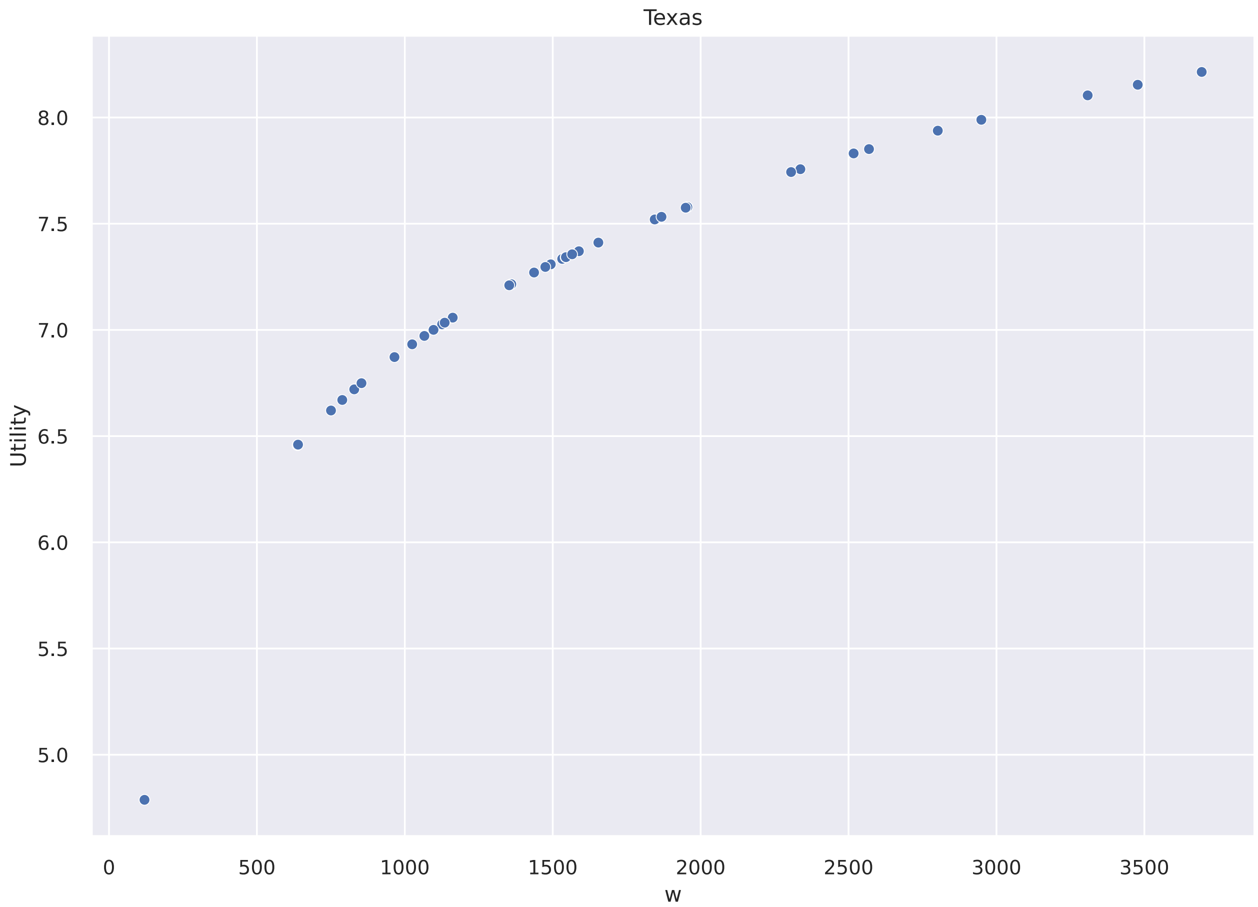


Texas

```
temp = df[df["State"] == "Texas"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Texas')
```

```
Text(0.5, 1.0, 'Texas')
```

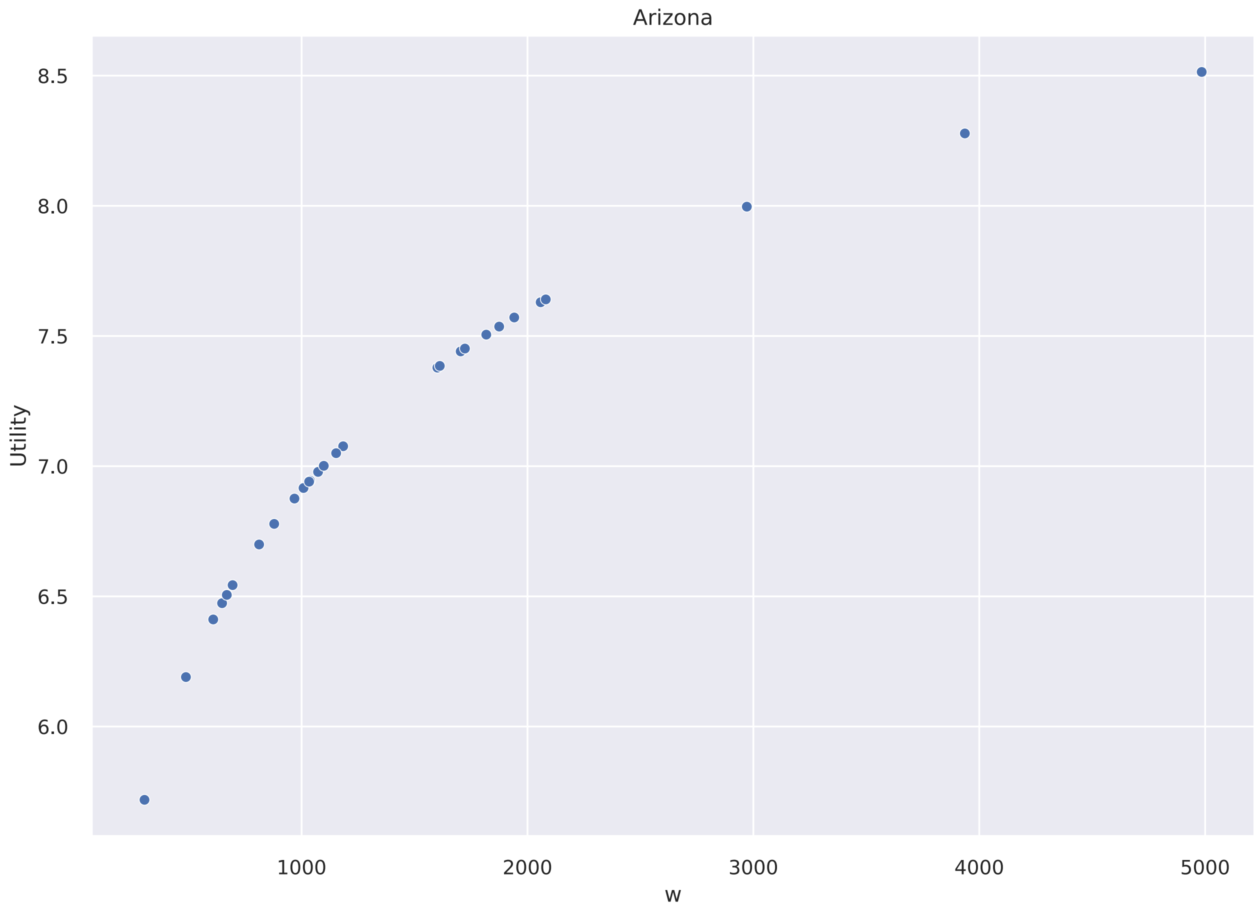


Arizona

```
temp = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

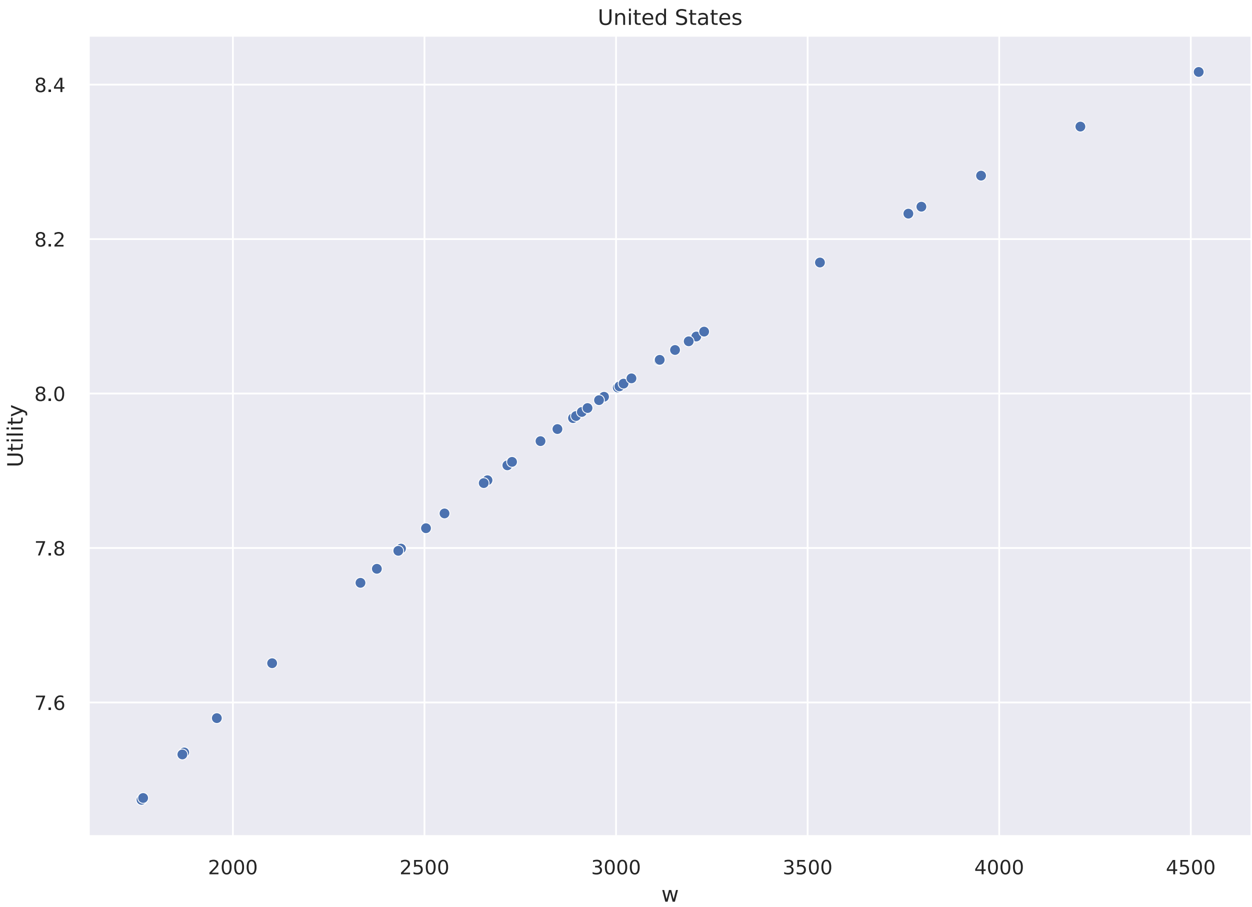


United States

```
temp = df[df["State"] == "United States"]
plot_df = pd.DataFrame()
plot_df["w"] = temp["Return per acre"]
plot_df["Utility"] = np.log(temp["Return per acre"])
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



CRRA Utility - Power

- Power: $U = \{1/(1 − r)\} w^{(1 − r)}, w > 0$

  for which $r_{r}(w) = r$ and $r_{a} = r/w$

Grapefruit

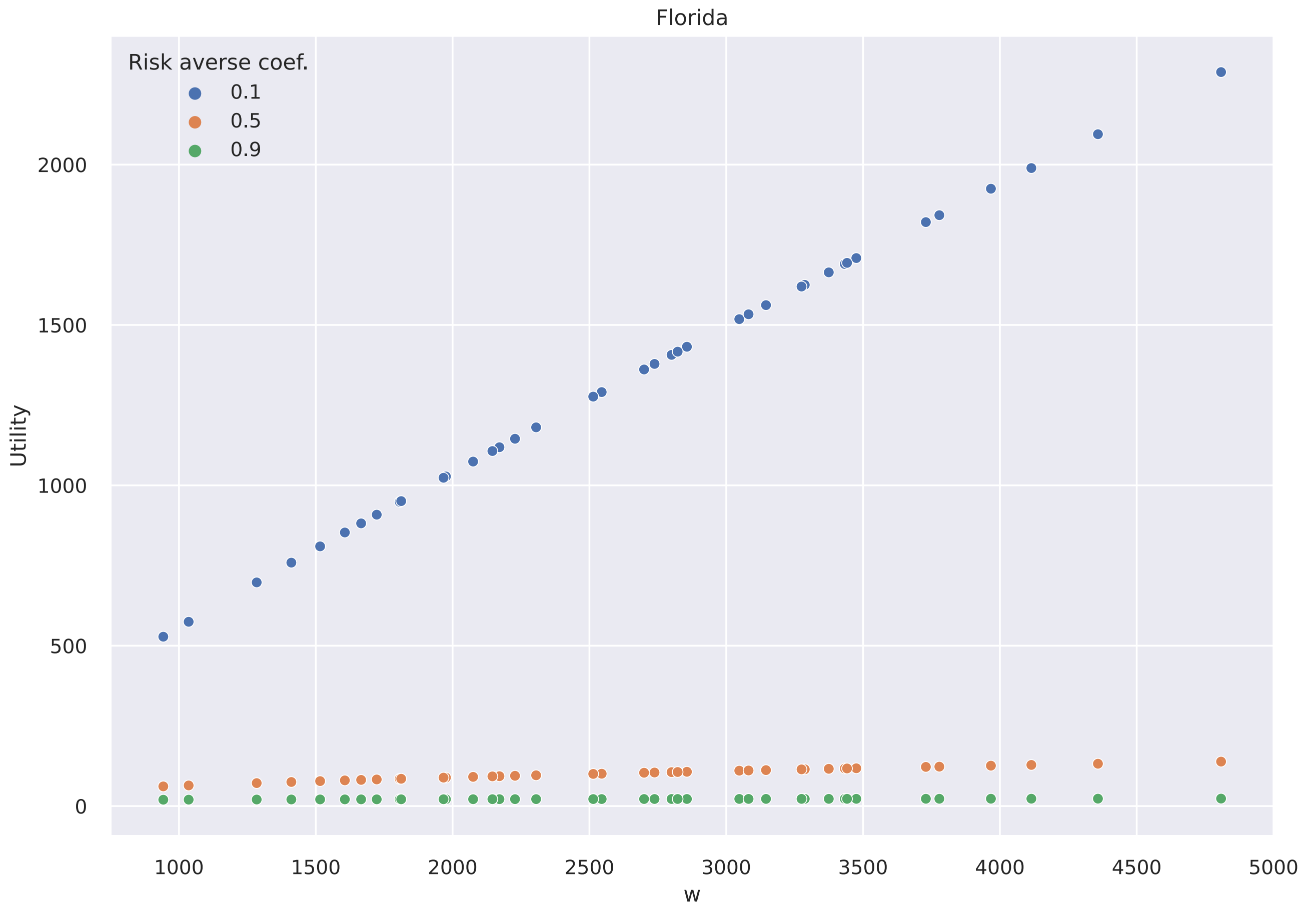
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Grapefruit")
```

Florida

```
sub_df = df[df["State"] == "Florida"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Florida')
```

```
Text(0.5, 1.0, 'Florida')
```

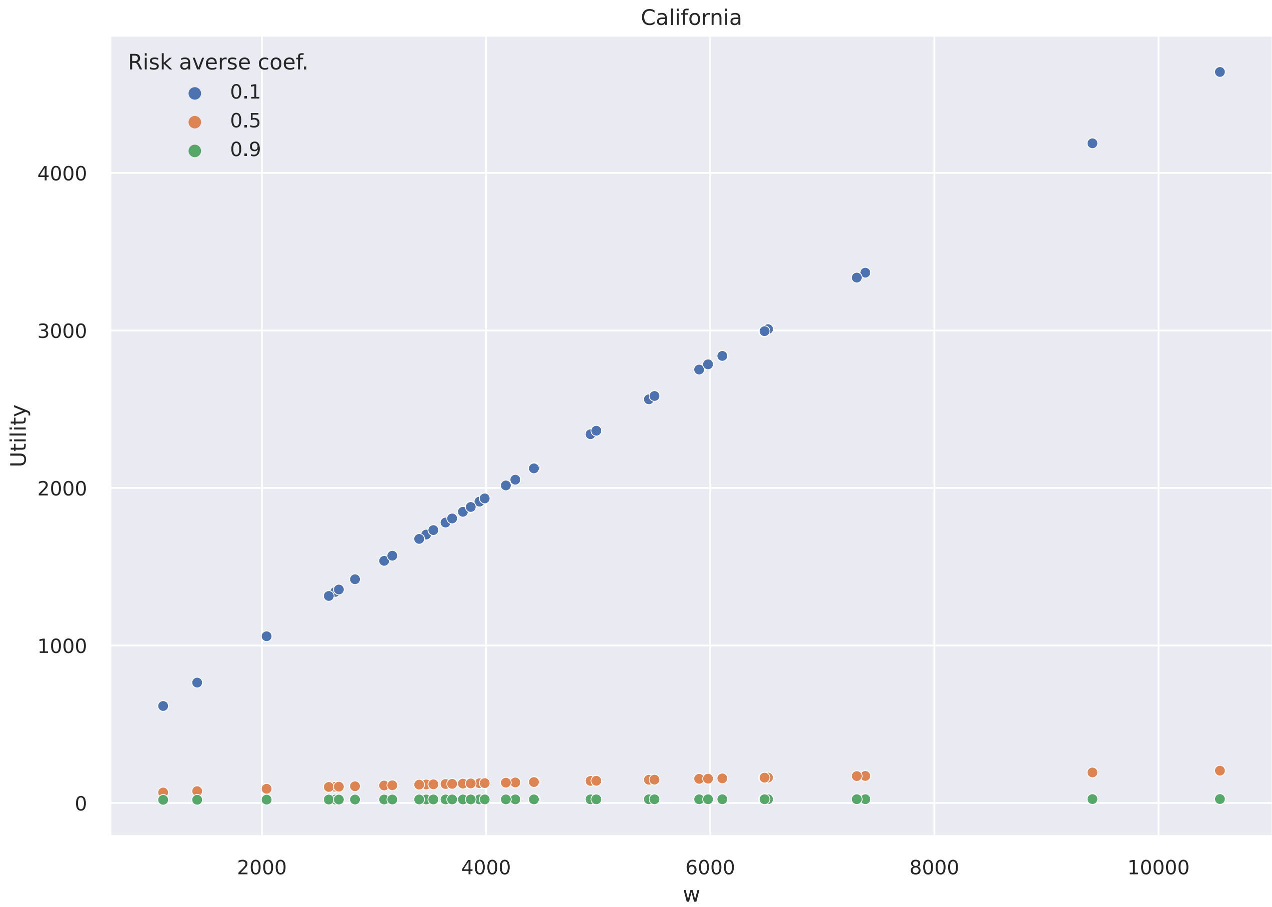


California

```
sub_df = df[df["State"] == "California"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

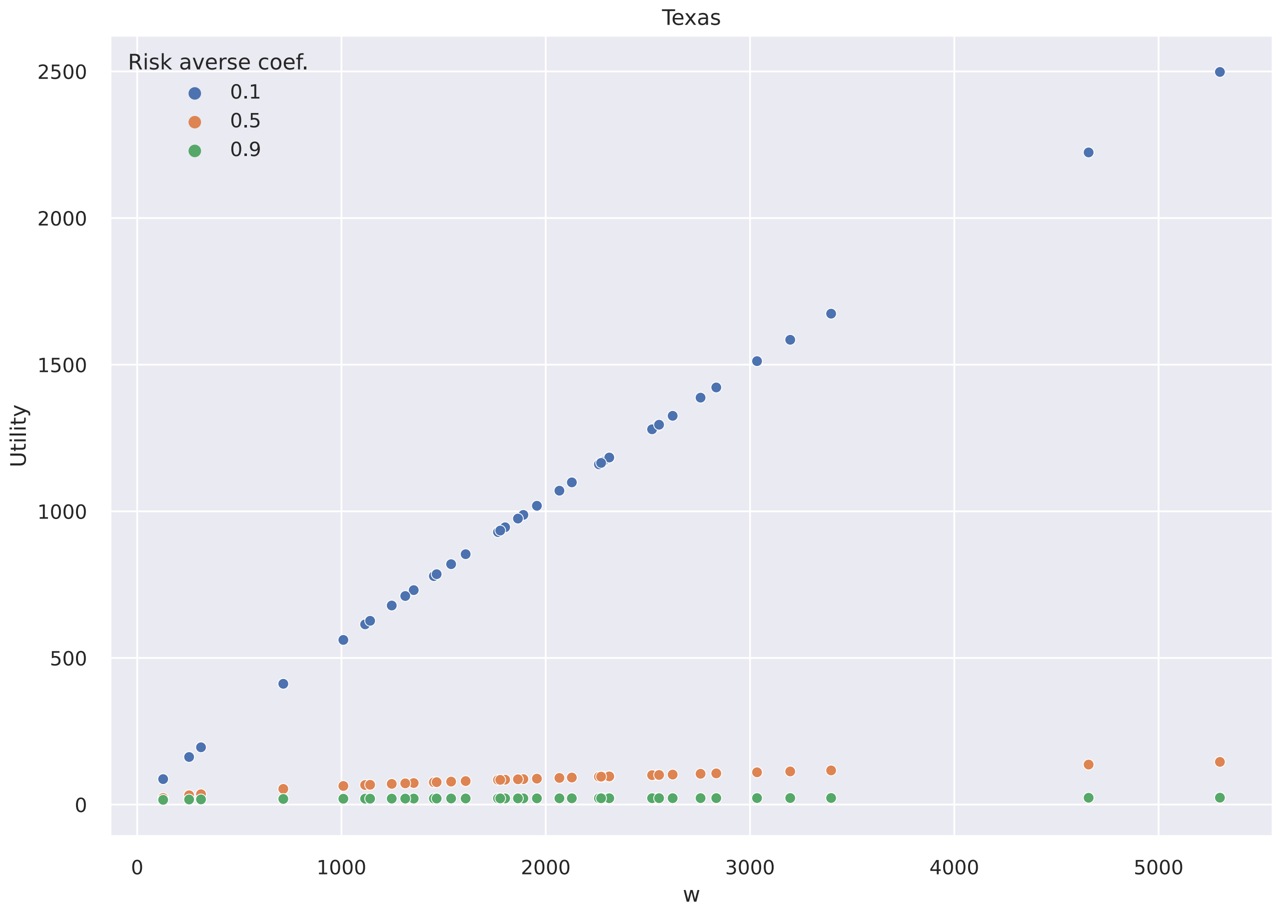


Texas

```
sub_df = df[df["State"] == "Texas"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Texas')
```

```
Text(0.5, 1.0, 'Texas')
```

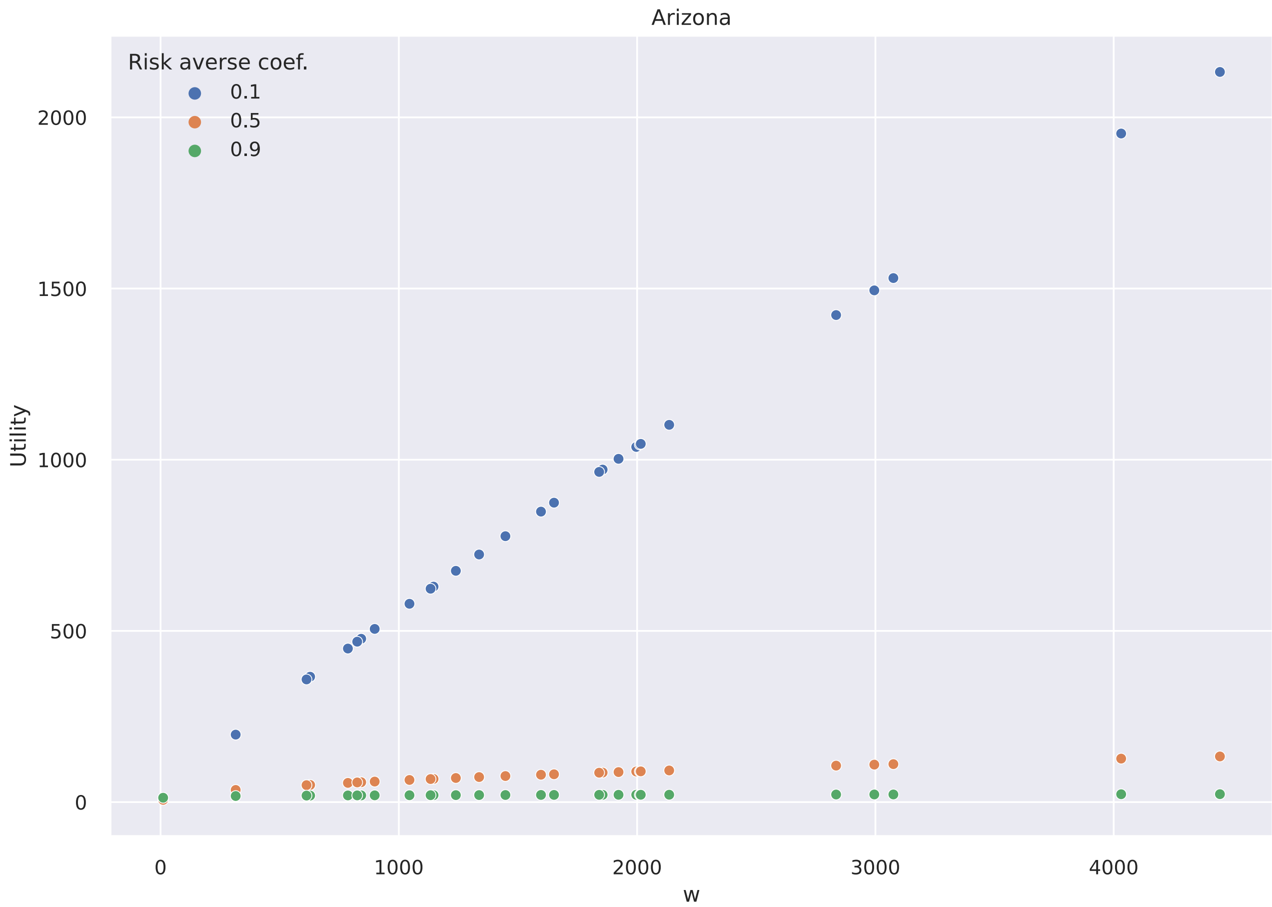


Arizona

```
sub_df = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

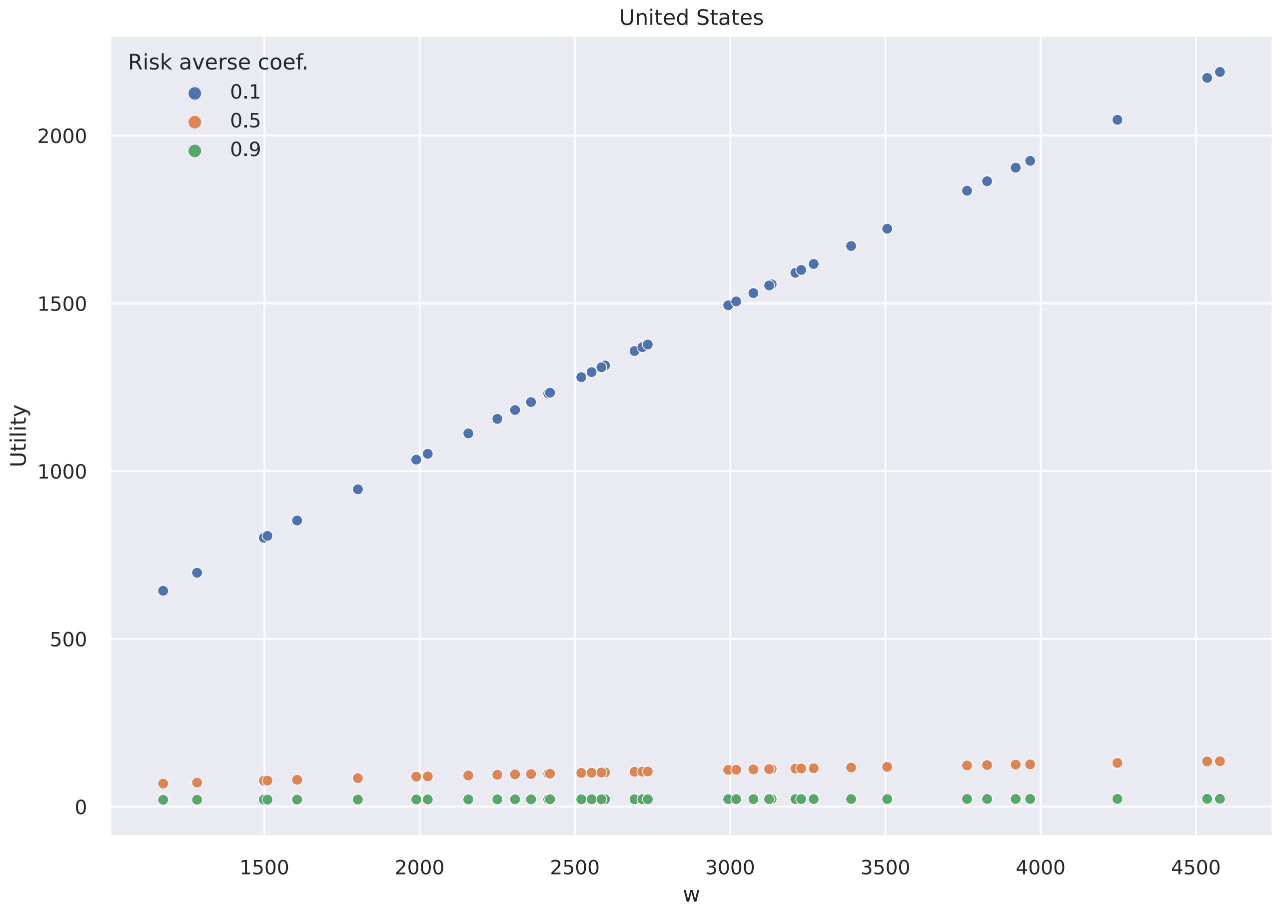


United States

```
sub_df = df[df["State"] == "United States"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Lemon

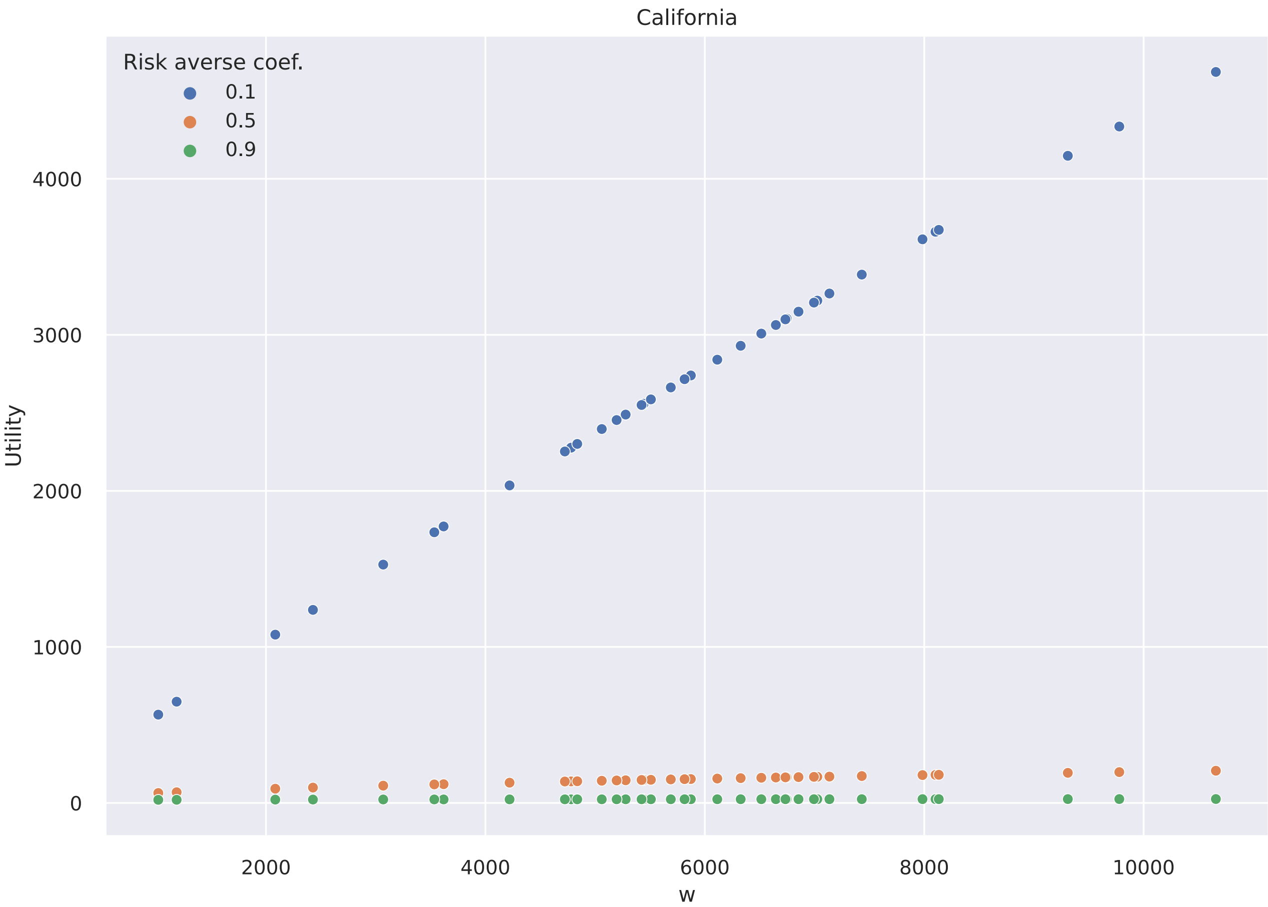
```python
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Lemon")
```

California

```python
sub_df = df[df["State"] == "California"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```python
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

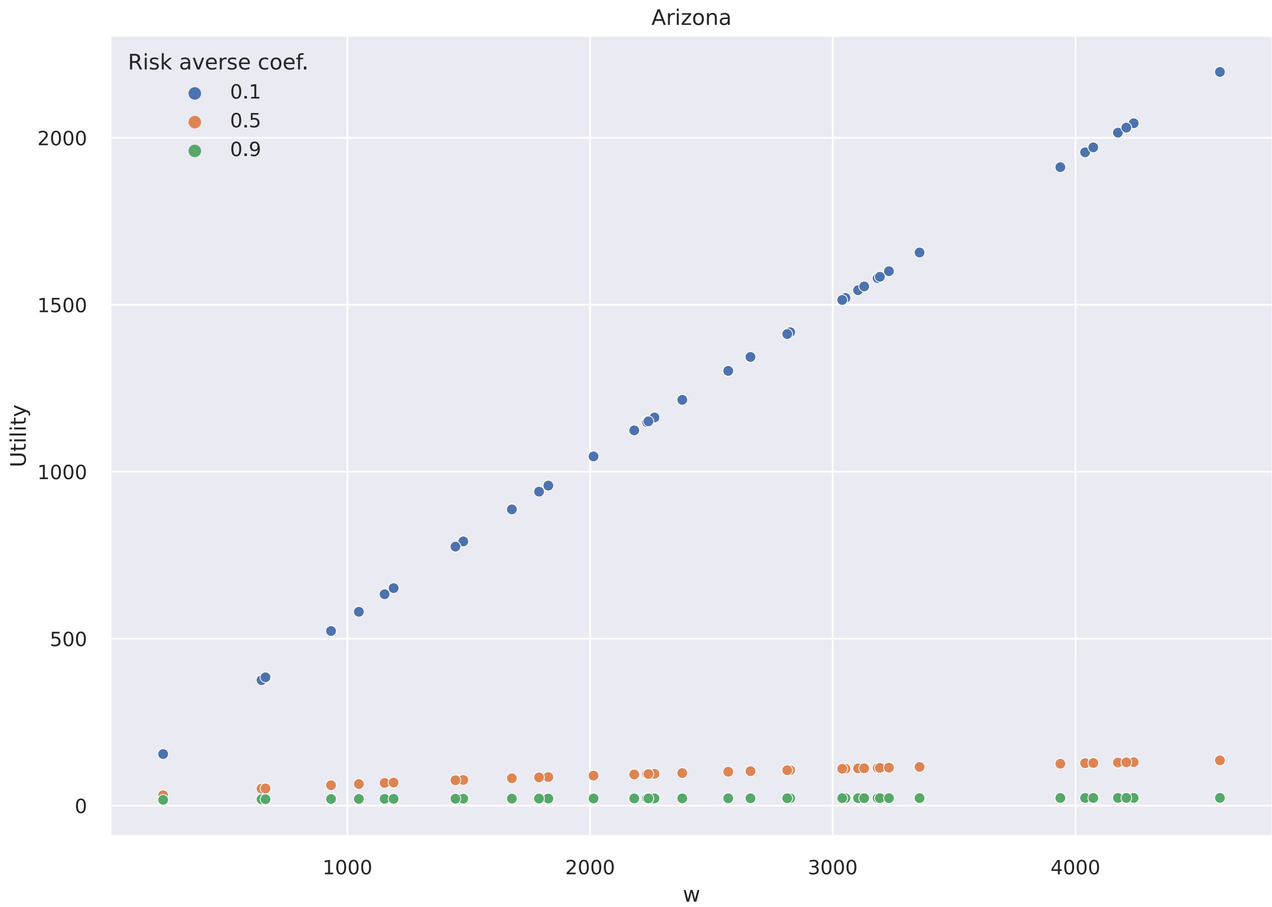


Arizona

```python
sub_df = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```python
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

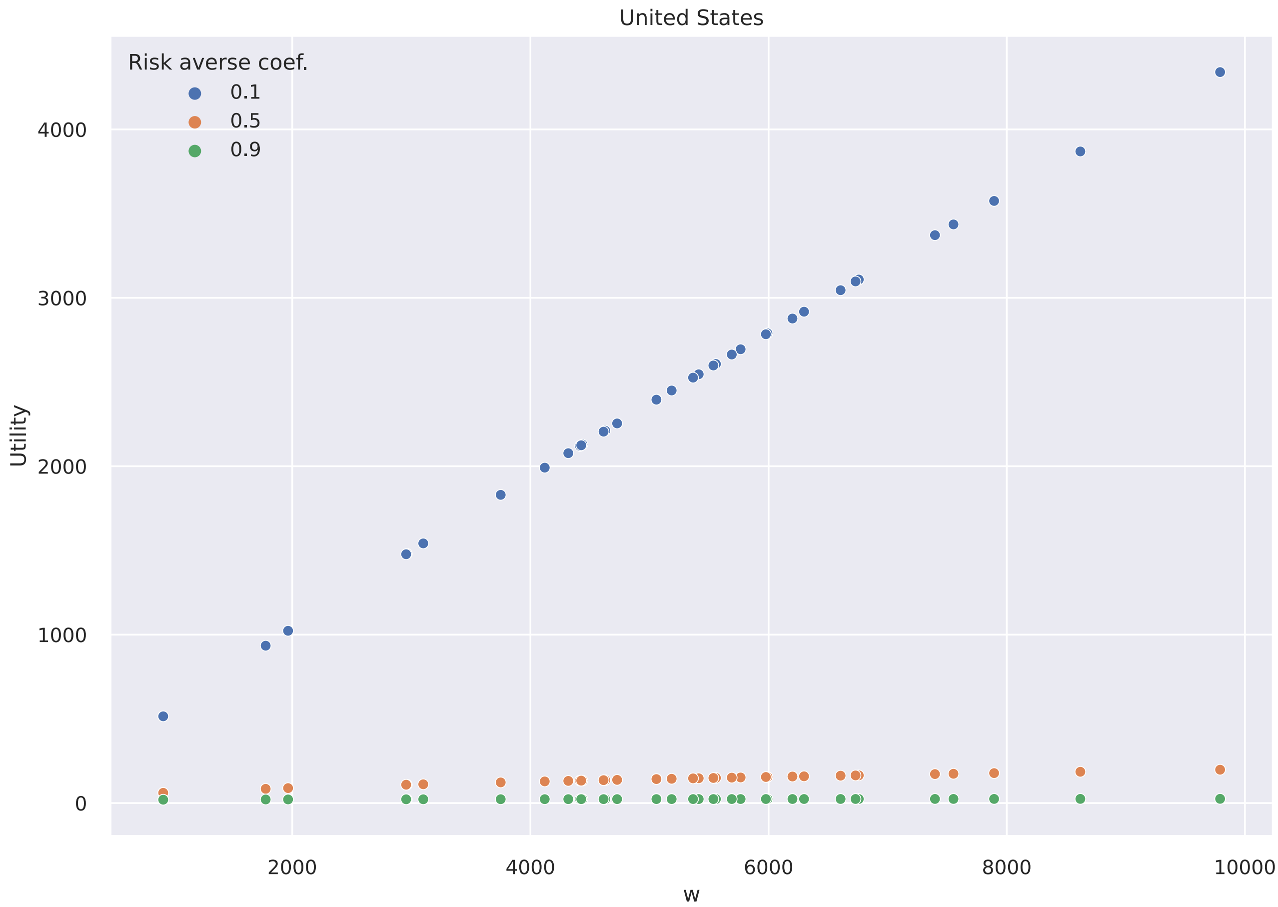


United States

```python
sub_df = df[df["State"] == "United States"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```python
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Orange

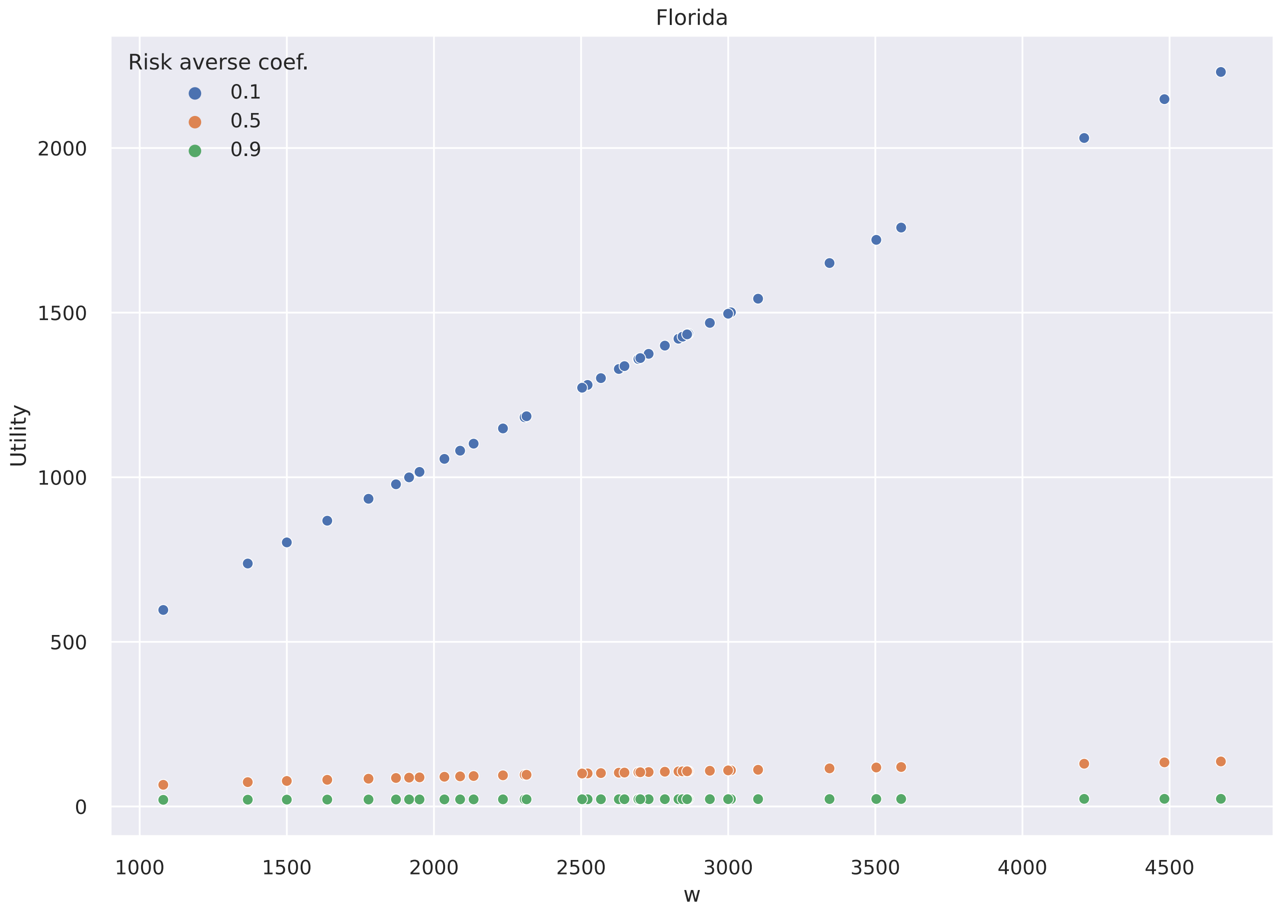
```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Orange")
```

Florida

```
sub_df = df[df["State"] == "Florida"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Florida')
```

```
Text(0.5, 1.0, 'Florida')
```

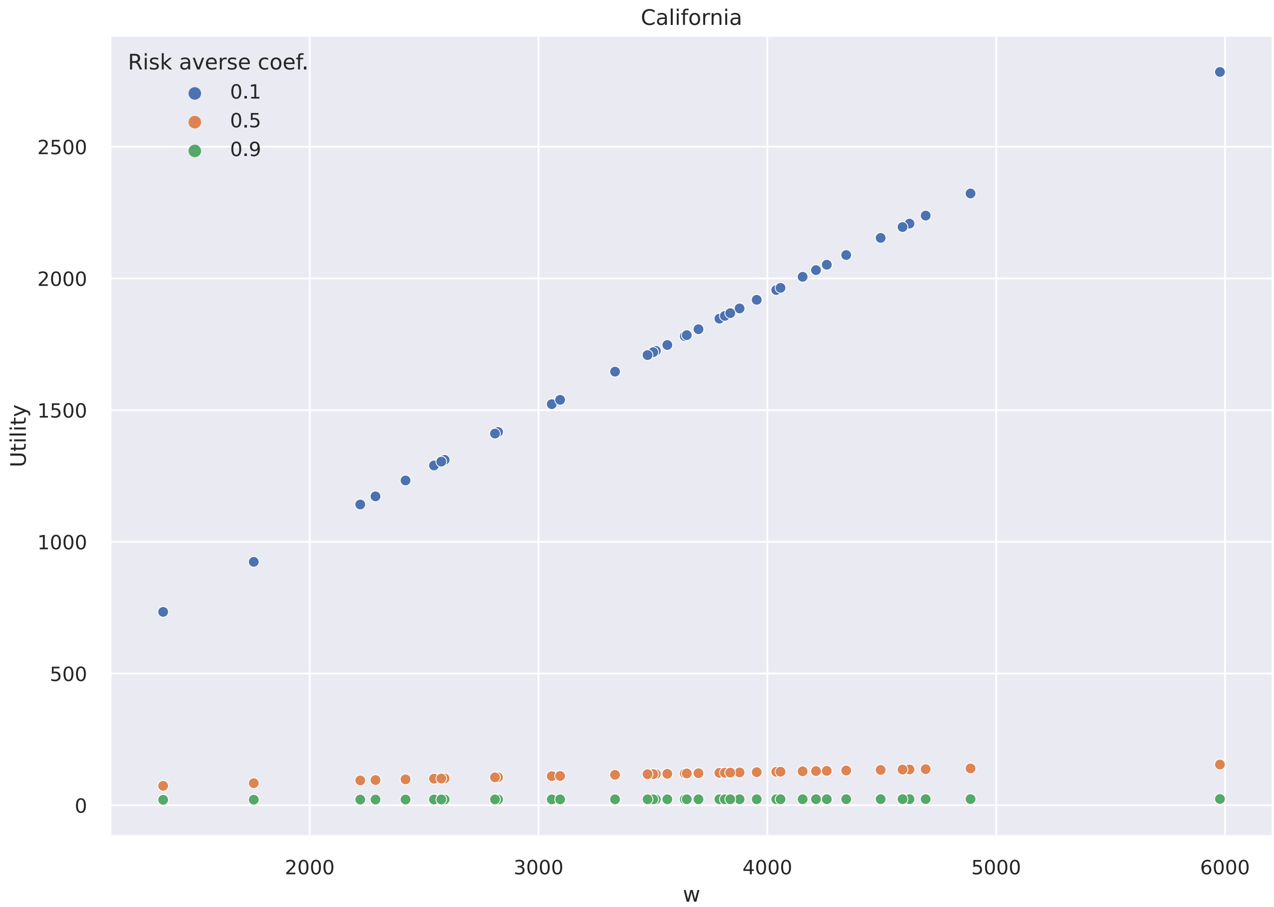


California

```
sub_df = df[df["State"] == "California"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('California')
```

```
Text(0.5, 1.0, 'California')
```

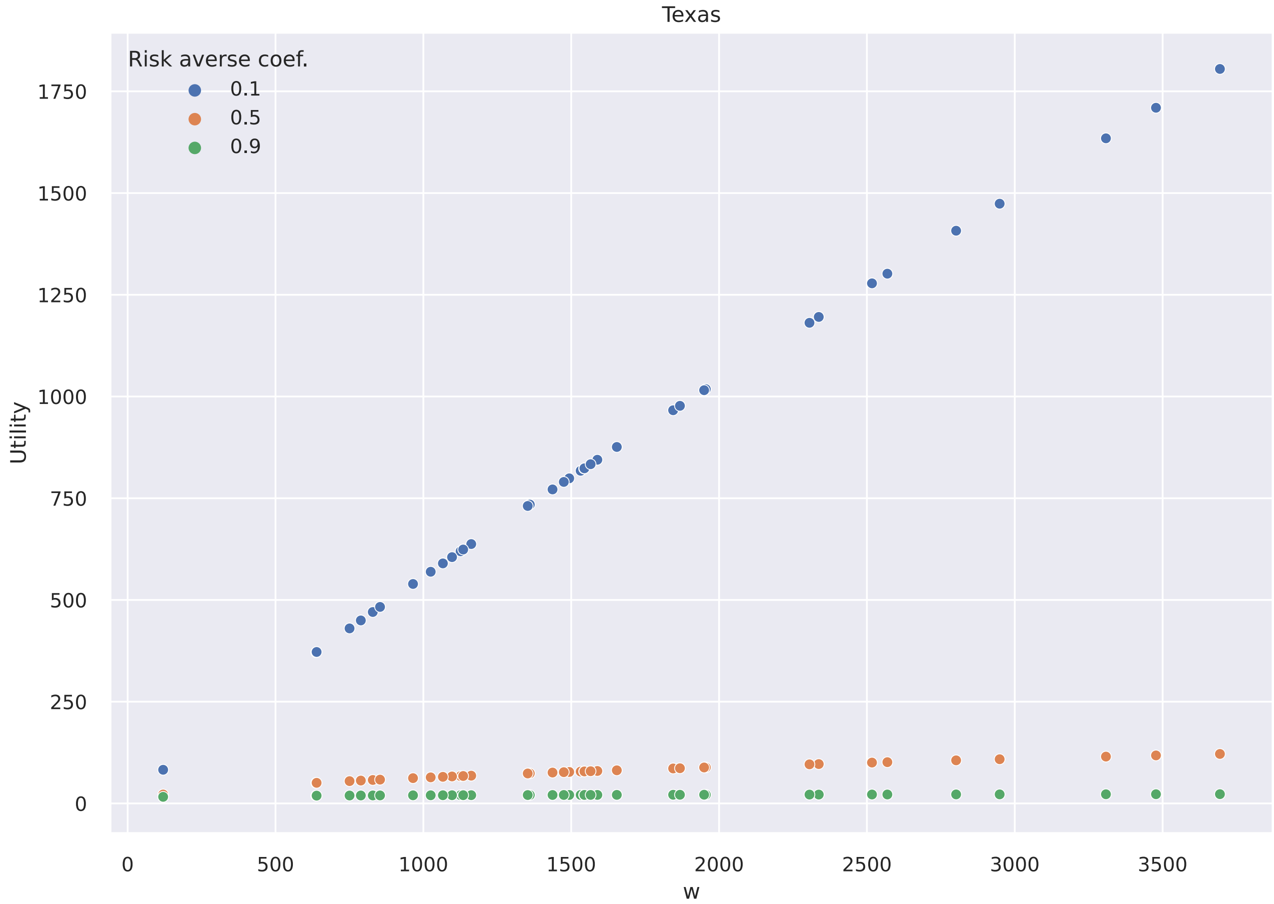


Texas

```
sub_df = df[df["State"] == "Texas"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Texas')
```

```
Text(0.5, 1.0, 'Texas')
```

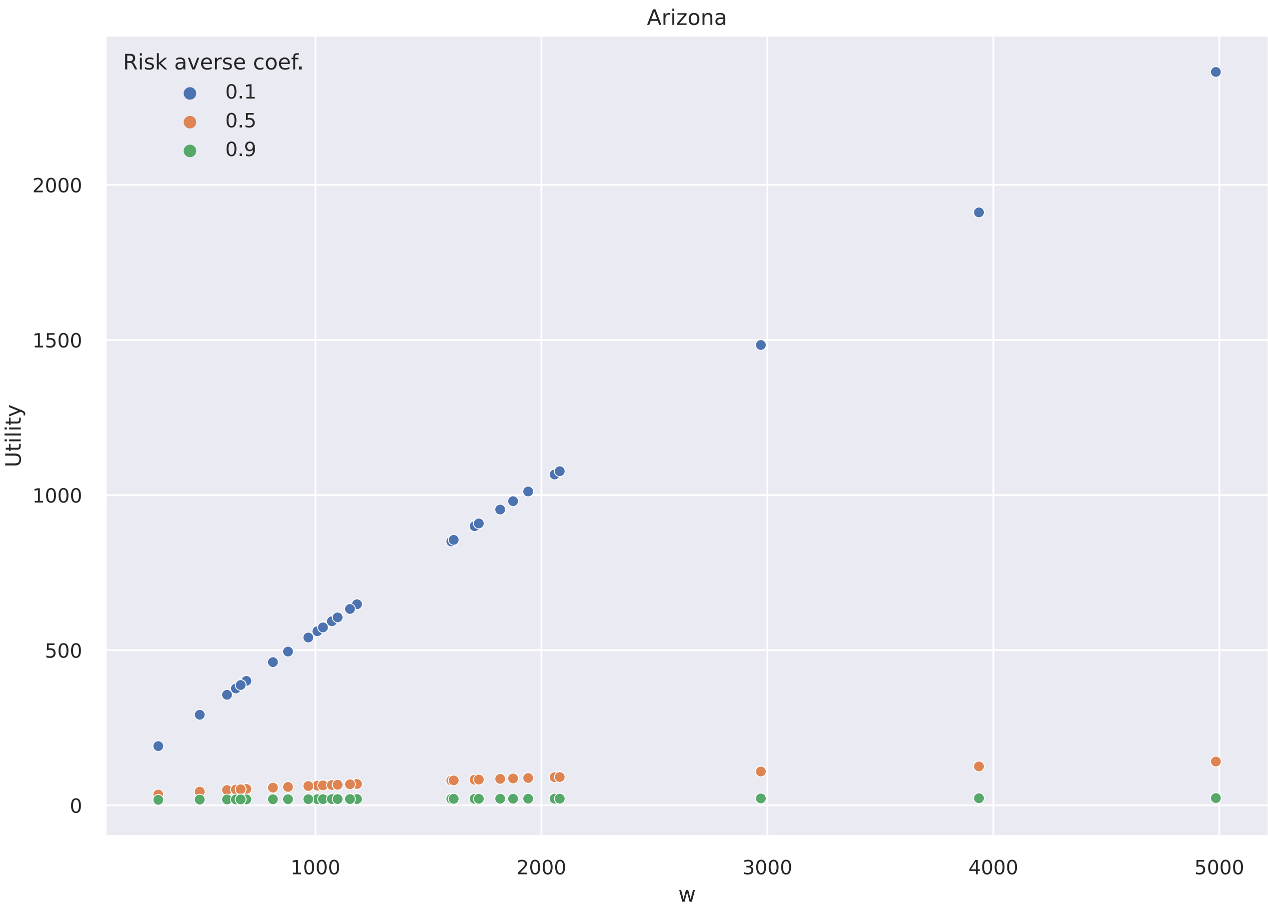


Arizona

```
sub_df = df[df["State"] == "Arizona"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('Arizona')
```

```
Text(0.5, 1.0, 'Arizona')
```

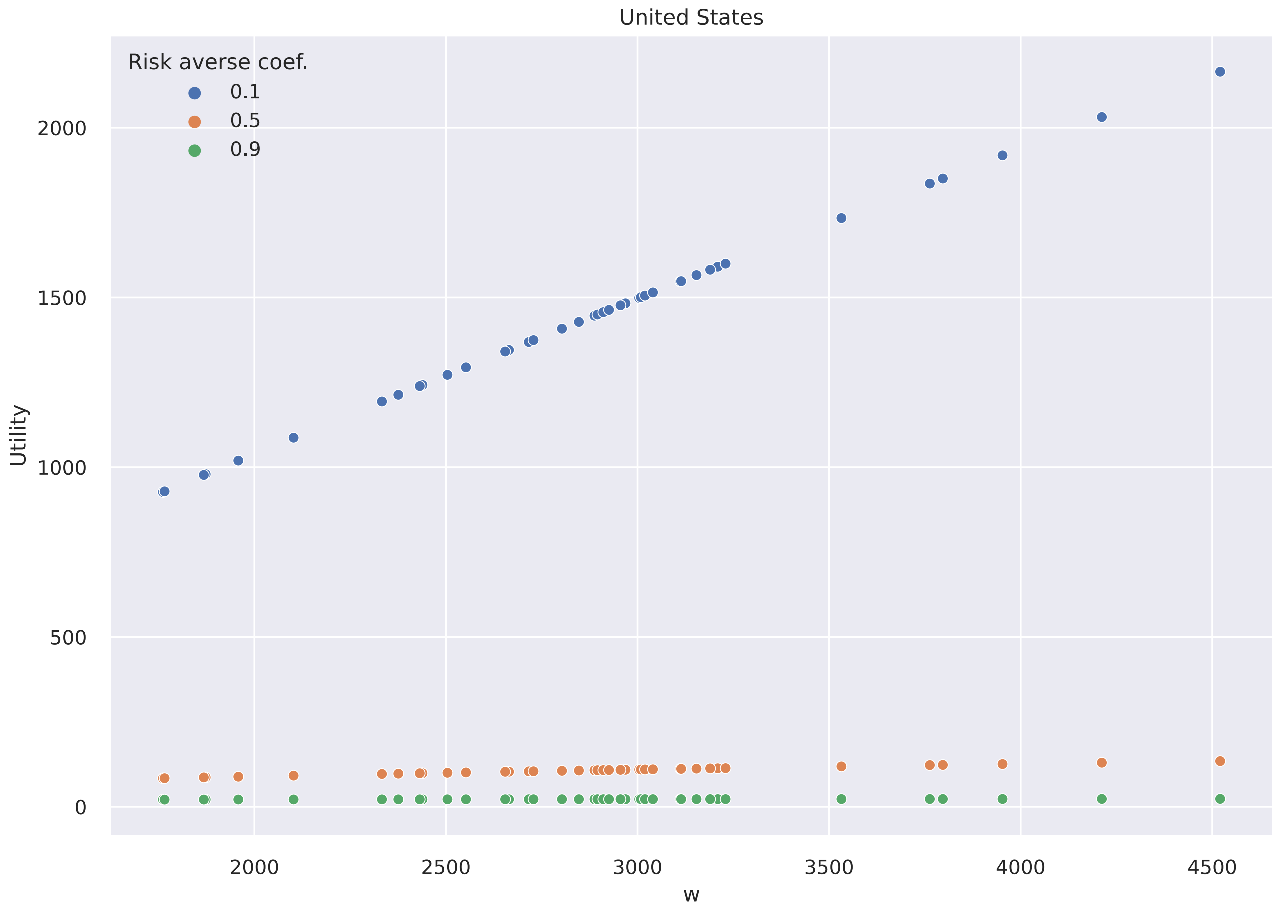


United States

```
sub_df = df[df["State"] == "United States"]
plot_df = pd.DataFrame(columns=["w", "Utility", "Risk averse coef."])
# r: 0.1
temp_utility = (1/(1 - 0.1)) * sub_df["Return per acre"] ** (1 - 0.1)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.1})
plot_df = plot_df.append(temp)
# r: 0.5
temp_utility = (1/(1 - 0.5)) * sub_df["Return per acre"] ** (1 - 0.5)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.5})
plot_df = plot_df.append(temp)
# r - 0.9
temp_utility = (1/(1 - 0.9)) * sub_df["Return per acre"] ** (1 - 0.9)
temp = pd.DataFrame({"w": sub_df["Return per acre"], "Utility": temp_utility, "Risk averse coef.": 0.9})
plot_df = plot_df.append(temp)
```

```
sns.scatterplot(data=plot_df, x="w", y="Utility", hue="Risk averse coef.", palette="deep").set_title('United States')
```

```
Text(0.5, 1.0, 'United States')
```



Explain

- Q1: `CARA` 和 `CRRA - Power` 都可以用來 `examine the utility levels with different levels of risk aversion`
- Q2: 只有 `CRRA - Logarithmic` 可以在同一個水果的限制下比較不同的州，因為其 Utility函式中僅包含變數 `w` ，相較於其他函式中都有一個以上的變動因素，多因素同時在變動時是無法比較的

Question 4

> As a thinking practice, if both Junior and Senior have the capital to choose their planting location, to choose which variety of Citrus fruit, and to choose which utilization will give the best economic performance. Suppose now the preferences are unknown and there is no best function to be used to characterize the production phase. What kind of graph will we need to generate to show the comparison across different risky prospects to aim for a stochastic dominance analysis, either it's first- or second-degree? Use command cumul to generate the probabilistic distribution of the outcome variable. Put down your graphs, as accurately as you can, and identify the likely choices facing Junior and Senior. Briefly state your reason, and list out all the possible scenarios that you think most relevant for discussion.

我們可以使用 CDF 圖進行stochastic dominance analysis

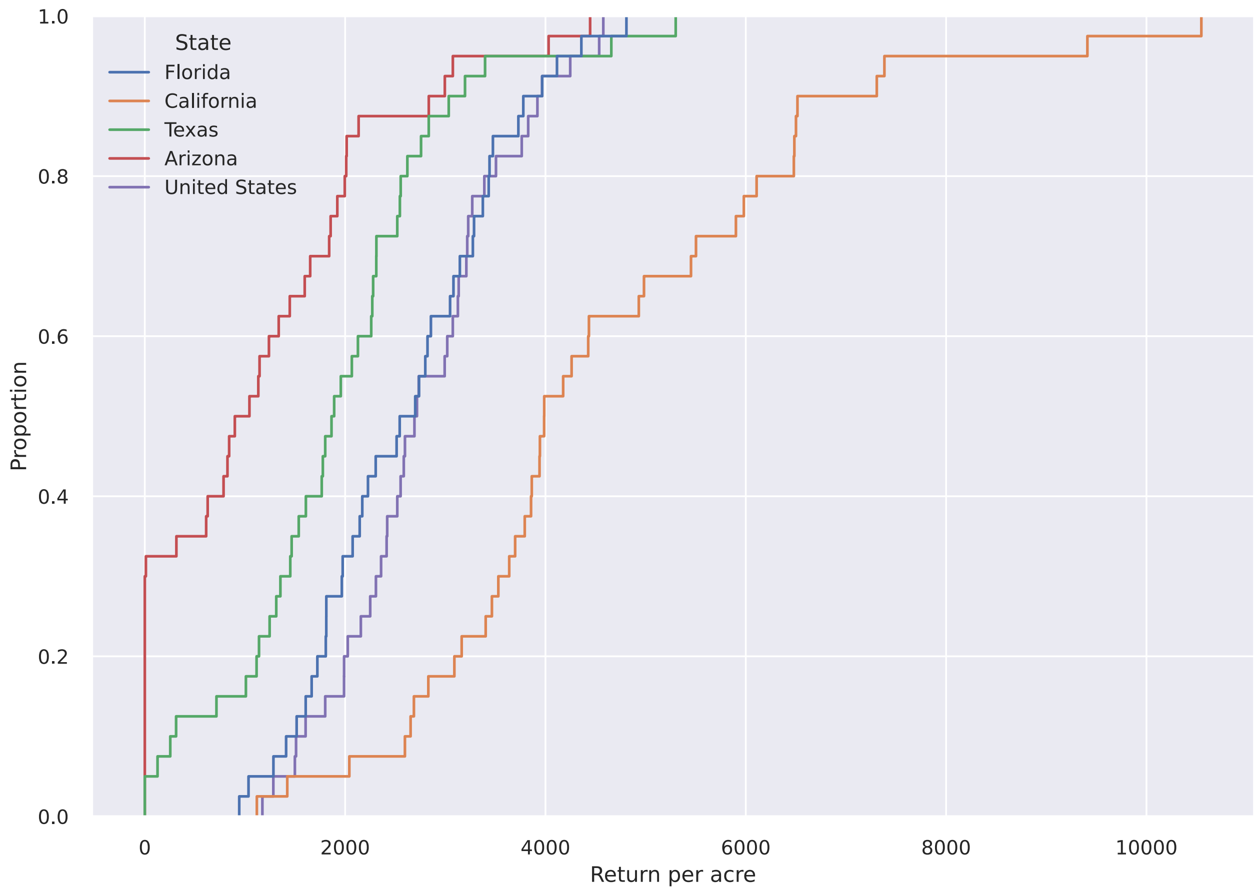
CDF

Grapefruit

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Grapefruit")
# Fill N/A with 0
df = df.fillna(0)
```

```
sns.ecdfplot(data=df, x="Return per acre", hue="State")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fed5ba90>
```

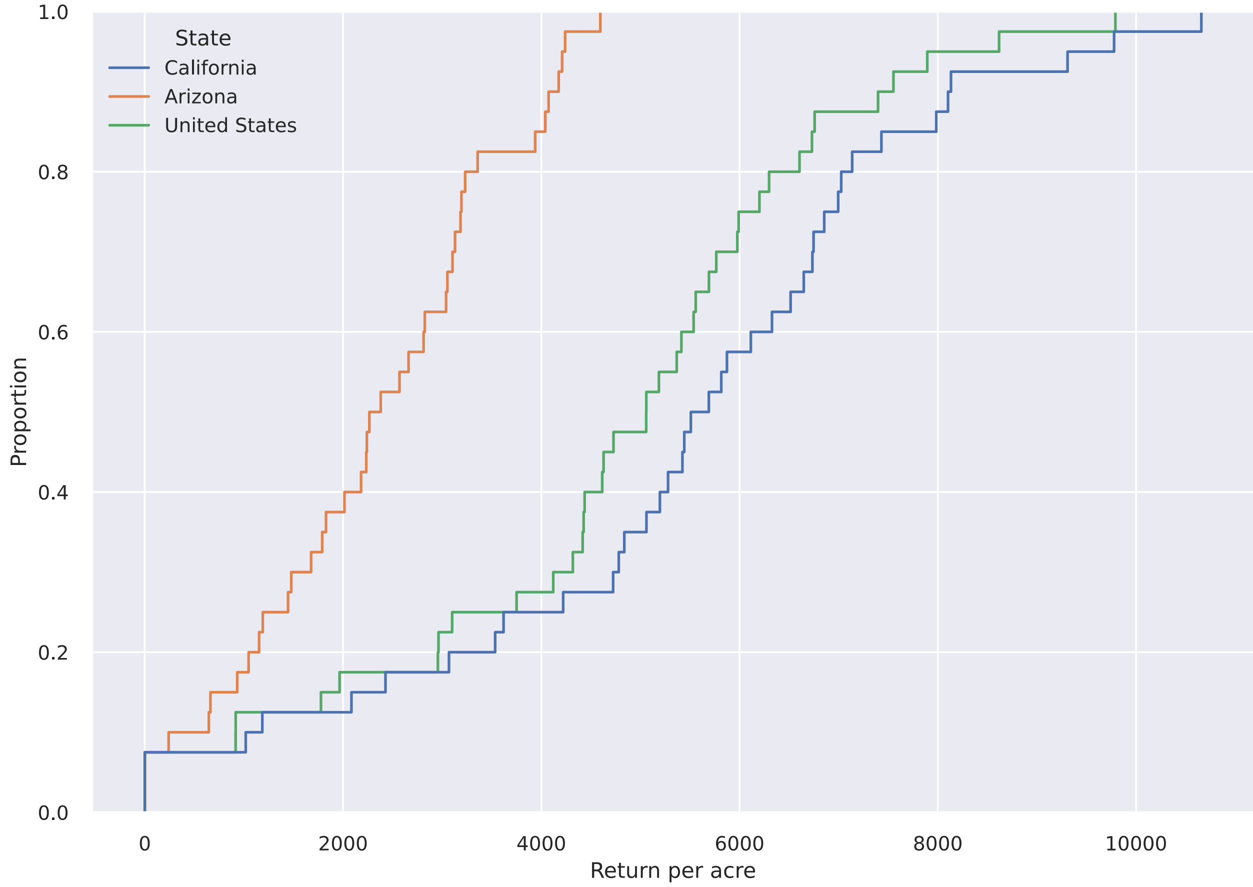


Lemon

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Lemon")
# Fill N/A with 0
df = df.fillna(0)
```

```
sns.ecdfplot(data=df, x="Return per acre", hue="State")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4ffe9fa50>
```

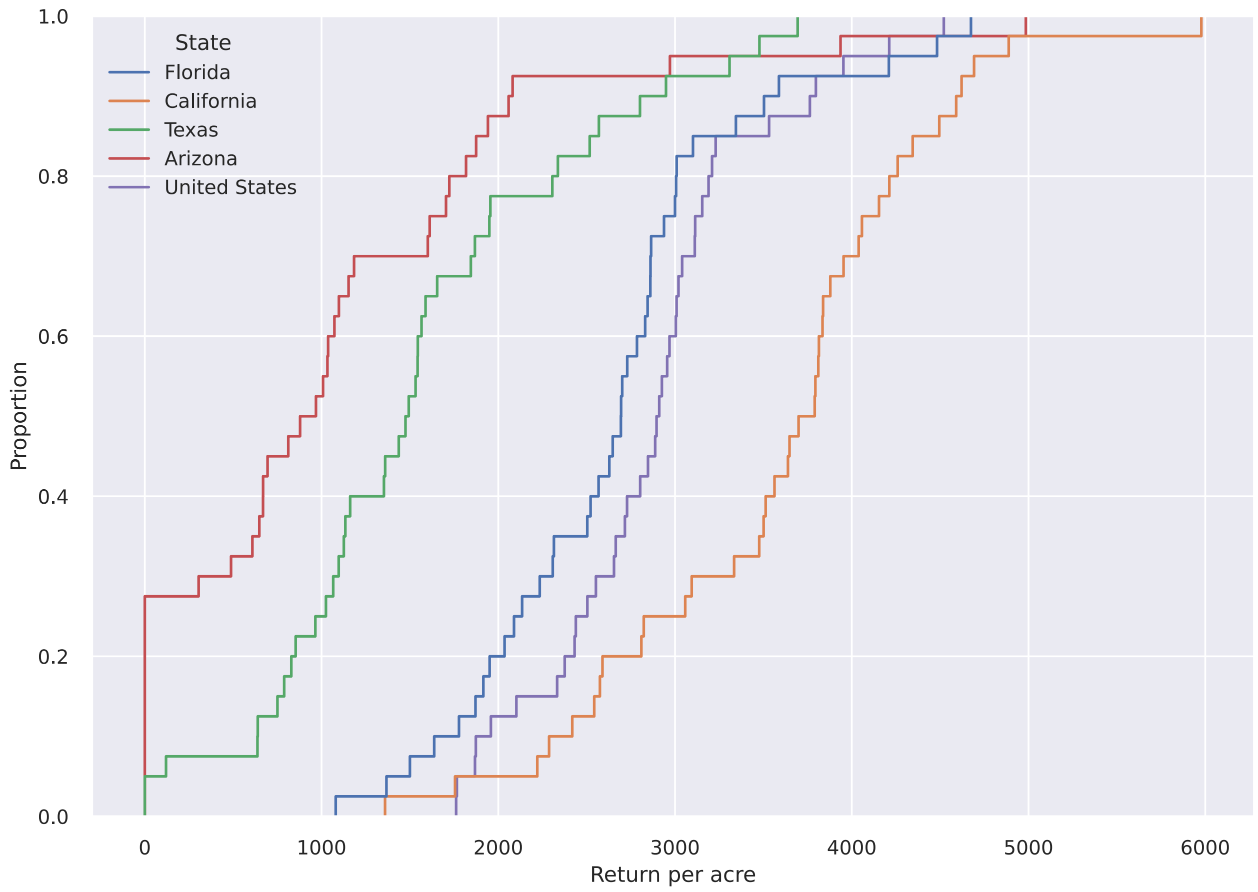


Orange

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Return per acre.xlsx", sheet_name="Orange")
# Fill N/A with 0
df = df.fillna(0)
```

```
sns.ecdfplot(data=df, x="Return per acre", hue="State")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4ff299590>
```



Explain

在上面個作物之CDF圖中，`First-degree stochastic dominance (FSD)` 僅能在線段不交會的情況下進行比較，換句話說，如 `Grapefruit` 中 `Florida` 和 `United States` 線段有交會到，在FSD下兩者並無法比較得知誰較優；而在 `Second-degree stochastic dominance (SSD)` 下，SSD 在 FSD 之上更近一步比較兩條線的底下的面積，解決了部分情況在FSD下無法比較的窘境。
當然了，`SSD` 亦有其限制存在，也有人提出 `TSD` 解決方案，但 TSD 的成效並不如 SSD 之於 FSD 般明顯，故我們並未使用 TSD 進行分析。

Question 5

> **Seasonal prices** for fruits is critical - Go to the data on per-box monthly equivalent- on-tree returns: Focus on grapefruit in California, given the fact that the marketing season start from 11/1 in previous year to 10/31 in the next year, what could it imply for fluctuation in prices? Compared with its yield data, which month(s) most accurately depict the classic relationship between supply price and quantity? What are the possible risks facing citrus fruit growers? Could we locate the risk corresponding to the dropping yields at certain point of time?

> Set up a simulation program to simulate the price given 100 observations, following a lognormal distribution. Show the summary statistics from your experiment. Can we truly replicate the original price series pattern from September to December by performing the experiment 1000 times? (Play some try-and-error.)

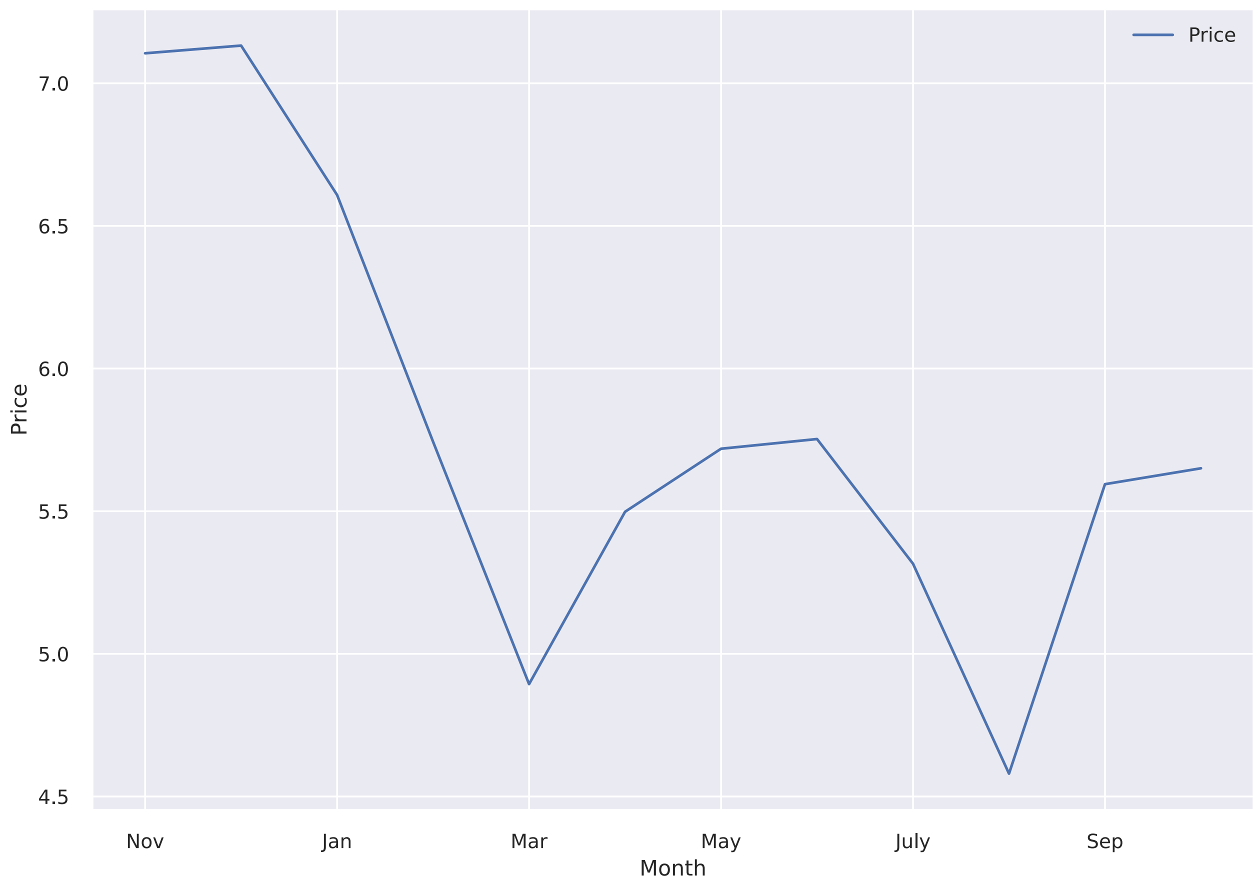
Fluctuation in prices

從 Annual Summary 的資訊中我們可以得知，**1月底至2月份可能會發生霜害**，進而影響產量，農產 time lag 的特性使得價格到3月份後才顯現在價格上；而**8, 9月的颶風** 也會使得價格上漲

```
# PPI
ppi_df = pd.read_excel("gdrive/MyDrive/風險管理/PPI.xlsx", sheet_name="PPI")
ppi = ppi_df["2015 base PPI"]
```

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Trend.xlsx", sheet_name="Month Trend")
del df["Year"]
del df["Unnamed: 13"]
del df["Unnamed: 14"]
df = df.iloc[:40]
plot_data = {}
for each in df:
    plot_data[each] = (df[each] * ppi).mean()
    df[each] *= ppi
pd.DataFrame.from_dict(plot_data, orient='index', columns=["Price"]).plot.line(xlabel="Month", ylabel="Price")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fefd6310>
```



Which month(s) most accurately depict the classic relationship between supply price and quantity?

從資料中我們可以觀察到，`June` 和 `July` 和年度價格的 MSE 是最小的 (其中 `June: 2.438984`) 是最小的

故我們選擇使用 `June` 作為代表月份

```python
df = pd.read_excel("gdrive/MyDrive/風險管理/Trend.xlsx", sheet_name="Year Trend")
del df["Year"]

result = pd.DataFrame(columns=["Month", "MSE"])

for each in df.columns[1:]:
    # Fill N/A with mean
    df[each] = df[each].fillna(df[each].mean())
    temp = pd.DataFrame({"Month": each, "MSE": mean_squared_error(df["California"] * ppi[:40], df[each]* ppi[:40])}, index=[0])
    result = result.append(temp)
result
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Month	MSE
0	Nov	12.907137
0	Dec	13.807945
0	Jan	11.542190
0	Feb	8.959618
0	Mar	5.348832
0	Apr	4.505816
0	May	3.244188
0	June	2.438984
0	July	2.860963
0	Aug	6.658194
0	Sep	6.103804
0	Oct	7.164386

What are the possible risks facing citrus fruit growers? Could we locate the risk corresponding to the dropping yields at certain point of time?

Possible risk:

1. 黃龍病
2. 霜害
3. 颶風

氣候災害如 `霜害`, `颶風` 等會反映在價格上，我們可以從 `equivalent-on-tree returns` 資料中價格的波動上觀察到；而其他如黃龍病等是並無時間上的規律性，全年皆有可能發生，較難從資料中觀察得知

Simulation program

```
df = pd.read_excel("gdrive/MyDrive/風險管理/Trend.xlsx", sheet_name="Year Trend")
df = df[["Sep", "Oct", "Nov", "Dec"]]
# Fill N/A with mean
df = df.fillna(df.mean())

df.describe()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Sep	Oct	Nov	Dec
count	40.000000	40.000000	40.000000	40.000000
mean	7.559474	7.285789	8.627000	8.570750
std	3.962710	4.801986	4.901102	4.922928
min	1.030000	1.100000	1.650000	1.460000
25%	4.665000	4.062500	6.027500	5.935000
50%	7.490000	6.700000	7.755000	7.340000
75%	9.597500	9.175000	10.012500	9.670000
max	16.770000	24.120000	21.140000	21.740000

Sep

$\mu=7.559474, \sigma=3.962710$，當 $\mu=5.205, \sigma=4.049$ 的時候可以逼近原始資料長相

```python
# Random config
np.random.seed(seed)
mu, sigma = lognorm_params(5.205, 4.049)

result = pd.DataFrame(columns=["mean", "std"])

for _ in range(1000):
    randan_data = np.random.lognormal(mean=mu, sigma=sigma, size=100)
    result = result.append({"mean": np.mean(randan_data),
                            "std": np.std(randan_data)},
                           ignore_index=True)
result.describe()
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	mean	std
count	1000.000000	1000.000000
mean	7.557535	3.962626
std	0.399414	0.529427
min	6.505996	2.643479
25%	7.274400	3.607445
50%	7.541119	3.908389
75%	7.806487	4.285163
max	9.056363	6.545958

Oct

$\mu=7.285789, \sigma=4.801986$，當 $\mu=4.169, \sigma=4.396$ 的時候可以逼近原始資料長相

```python
# Random config
np.random.seed(seed)
mu, sigma = lognorm_params(4.169, 4.936)

result = pd.DataFrame(columns=["mean", "std"])

for _ in range(1000):
    randan_data = np.random.lognormal(mean=mu, sigma=sigma, size=100)
    result = result.append({"mean": np.mean(randan_data),
                            "std": np.std(randan_data)},
                           ignore_index=True)
result.describe()
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	mean	std
count	1000.000000	1000.000000
mean	7.285549	4.801161
std	0.486261	0.789710
min	6.009228	2.973378
25%	6.938390	4.255489
50%	7.255260	4.700910
75%	7.595594	5.241760
max	9.127089	9.406896

Nov

$\mu=8.627000, \sigma=4.901102$，當 $\mu=5.609, \sigma=5.017$ 的時候可以逼近原始資料長相

```python
# Random config
np.random.seed(seed)
mu, sigma = lognorm_params(5.609, 5.017)

result = pd.DataFrame(columns=["mean", "std"])

for _ in range(1000):
    randan_data = np.random.lognormal(mean=mu, sigma=sigma, size=100)
    result = result.append({"mean": np.mean(randan_data),
                            "std": np.std(randan_data)},
                           ignore_index=True)
result.describe()
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	mean	std
count	1000.000000	1000.000000
mean	8.627077	4.901085
std	0.494697	0.701625
min	7.324851	3.192434
25%	8.278142	4.421322
50%	8.601971	4.824585
75%	8.933656	5.318432
max	10.489914	8.545283

Dec

$\mu=8.570750, \sigma=4.922928$，當 $\mu=5.526, \sigma=5.04$ 的時候可以逼近原始資料長相

```python
# Random config
np.random.seed(seed)
mu, sigma = lognorm_params(5.526, 5.04)

result = pd.DataFrame(columns=["mean", "std"])

for _ in range(1000):
    randan_data = np.random.lognormal(mean=mu, sigma=sigma, size=100)
    result = result.append({"mean": np.mean(randan_data),
                            "std": np.std(randan_data)},
                           ignore_index=True)
result.describe()
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	mean	std
count	1000.000000	1000.000000
mean	8.570849	4.922224
std	0.496935	0.711496
min	7.262844	3.195312
25%	8.218392	4.435361
50%	8.545237	4.845823
75%	8.878236	5.343768
max	10.442961	8.649125

Question 6

> **Price ratio** - Go back to production data: First locate the new piece of information on grower price at the same place where you find the data for your Citrus Fruit study. Derive ratio of equivalent-on-tree returns and grower price. Several things to keep in mind: be aware of the difference between these two datasets, and find their common ground to generate this ratio. (You will need to look at the datasets closely to make things go smoothly.) ~~What's the type of ratio that can be derived to achieve the objective here? Refer to the Annual Report in the Folder again, interpret the ratio and its change over time.~~

> Set up a simulation program to simulate the ratio of prices from two datasets, suppose each sample comes from a lognormal distribution. The program requires six arguments as inputs. Set each sample observations of 100, use the mean and variance from actual data on the two price series stated above in your simulation. Simulate three types of ratio: Ratio of 10th percentile, ratio of mean, ratio of 90th percentile, with a 1000-times experiment. Show the summary statistics. Does the result change when we select new values for arguments for mean and variance for these two datasets, 0.7, 0.85, 0.08, 0.09?

Price ratio

從資料我們可以觀察到，`equivalent-on-tree returns` 和 `grower price` 間的比例和年份並無很明顯的關係，起起伏伏並無明顯規律

```python
df = pd.read_excel("gdrive/MyDrive/風險管理/Ratio.xlsx", sheet_name="Ratio")
df
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Year	Grower Price (Dollars / pounds)	US Fresh Equivalent-on-tree returns (Dollars / box)	Box weight (pounds)
0	1989/90	0.14	10.00	84.154023
1	1990/91	0.11	8.74	85.316420
2	1991/92	0.10	8.34	85.686844
3	1992/93	0.07	5.10	84.928946
4	1993/94	0.08	5.61	85.213107
5	1994/95	0.07	4.40	85.257496
6	1995/96	0.07	4.36	85.541338
7	1996/97	0.07	4.25	84.479476
8	1997/98	0.08	4.64	84.763685
9	1998/99	0.10	6.12	85.829833
10	1999/2000	0.08	6.84	87.253439
11	2000/01	0.07	5.10	84.765136
12	2001/02	0.08	5.43	84.530728
13	2002/03	0.10	6.33	85.292574
14	2003/04	0.07	7.23	84.276352
15	2004/05	0.23	18.79	83.125452
16	2005/06	0.19	13.96	84.320432
17	2006/07	0.14	10.03	86.422482
18	2007/08	0.11	9.29	85.740467
19	2008/09	0.09	7.87	84.977961
20	2009/10	0.12	11.41	84.343189
21	2010/11	0.12	10.85	87.128589
22	2011/12	0.14	11.04	87.108074
23	2012/13	0.11	10.15	86.326285
24	2013/14	0.13	11.95	85.559737
25	2014/15	0.14	11.81	85.815958
26	2015/16	0.19	16.63	85.462378
27	2016/17	0.21	18.83	85.218490
28	2017/18	0.28	21.67	83.487796
29	2018/19	0.26	20.68	83.994329
30	2019/20	0.19	18.18	85.458863

Grower Price 敘述統計

```
df["Grower Price (Dollars / pounds)"].describe()
```

```
count    31.000000
mean      0.127097
std       0.058889
min       0.070000
25%       0.080000
50%       0.110000
75%       0.140000
max       0.280000
Name: Grower Price (Dollars / pounds), dtype: float64
```

Fresh Equivalent-on-tree returns 敘述統計

```
(df["US Fresh Equivalent-on-tree returns (Dollars / box)"] / df["Box weight (pounds)"]).describe()
```

```
count    31.000000
mean      0.119687
std       0.061901
min       0.050308
25%       0.068569
50%       0.108350
75%       0.138644
max       0.259559
dtype: float64
```

```
ratio = df["Grower Price (Dollars / pounds)"] / (df["US Fresh Equivalent-on-tree returns (Dollars / box)"] / df["Box weight (pounds)"])
ratio_df = pd.DataFrame({"Year": df["Year"], "Ratio": ratio})
ratio_df
```

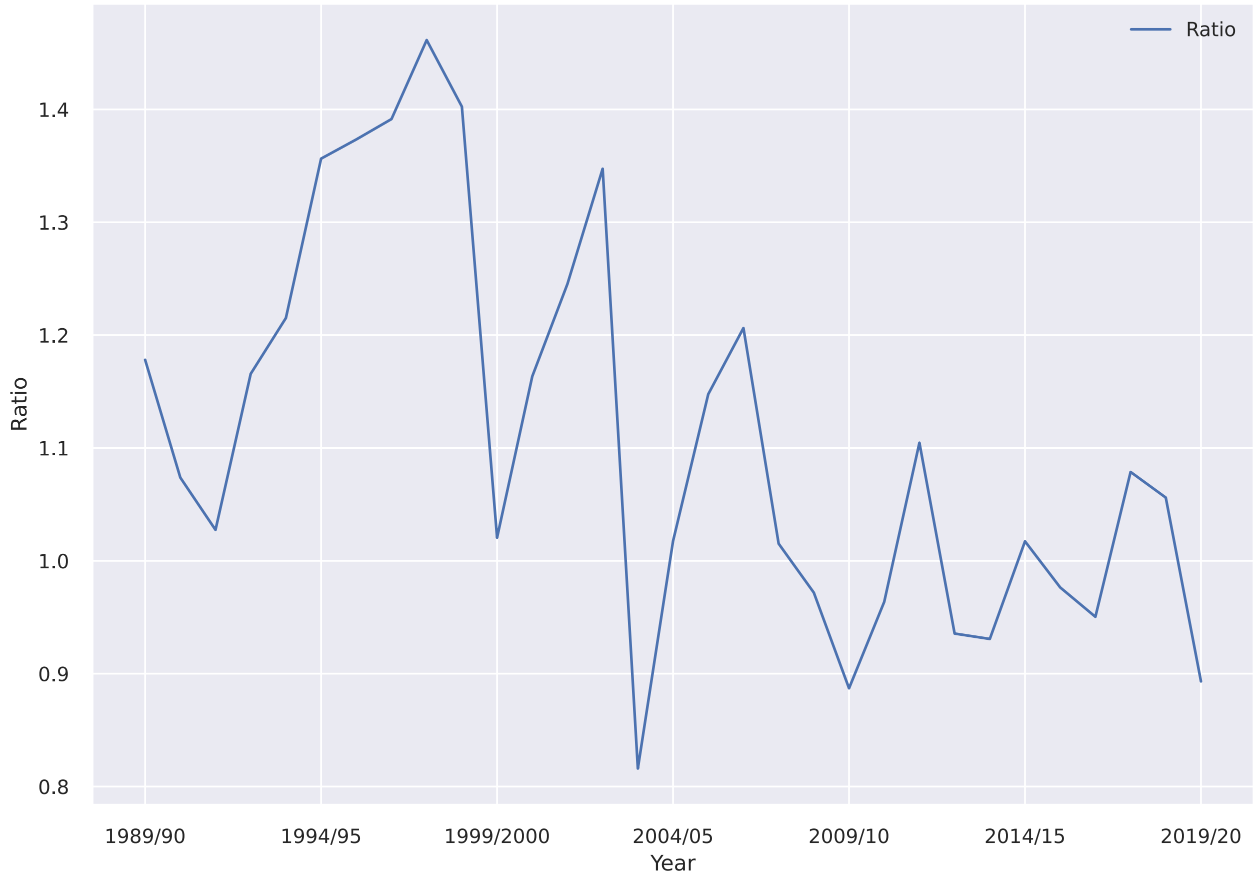
```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	Year	Ratio
0	1989/90	1.178156
1	1990/91	1.073776
2	1991/92	1.027420
3	1992/93	1.165691
4	1993/94	1.215160
5	1994/95	1.356369
6	1995/96	1.373370
7	1996/97	1.391427
8	1997/98	1.461443
9	1998/99	1.402448
10	1999/2000	1.020508
11	2000/01	1.163443
12	2001/02	1.245388
13	2002/03	1.347434
14	2003/04	0.815954
15	2004/05	1.017502
16	2005/06	1.147628
17	2006/07	1.206296
18	2007/08	1.015226
19	2008/09	0.971794
20	2009/10	0.887045
21	2010/11	0.963634
22	2011/12	1.104631
23	2012/13	0.935556
24	2013/14	0.930775
25	2014/15	1.017293
26	2015/16	0.976419
27	2016/17	0.950392
28	2017/18	1.078753
29	2018/19	1.056022
30	2019/20	0.893134

```
ratio_df.plot.line(x="Year", y="Ratio", xlabel="Year", ylabel="Ratio")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4ff5b6a10>
```



Simulation program

從結果中可以觀察到，$\mu_1=0.7, \sigma_1^2=0.08$ 和 $\mu_2=0.85, \sigma_2^2=0.09$ 的模擬結果相較原本的資料，其各個百分位距和平均數的 `mean` 和 `std` 都有明顯的下降，且從直方圖上觀察，資料似乎出現向左偏移的趨勢

$\mu_1=0.127, \sigma_1^2=0.058$, $\mu_2=0.12, \sigma_2^2=0.061$

```
# 固定seed
np.random.seed(seed)

result = pd.DataFrame(columns=["10th percentile", "mean", "90th percentile"])

for _ in range(1000):
    # 第一組數據
    mu, sigma = lognorm_params(0.127, 0.058)
    random_one = np.random.lognormal(mean=mu, sigma=sigma, size=100)
    # 第二組數據
    mu, sigma = lognorm_params(0.12, 0.061)
    random_two = np.random.lognormal(mean=mu, sigma=sigma, size=100)

    result = result.append({"10th percentile": np.percentile(random_one, 10) / np.percentile(random_two, 10),
                            "mean": np.mean(random_one) / np.mean(random_two),
                            "90th percentile": np.percentile(random_one, 90) / np.percentile(random_two, 90)},
                           ignore_index=True)

pd.DataFrame.from_dict(result).describe()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

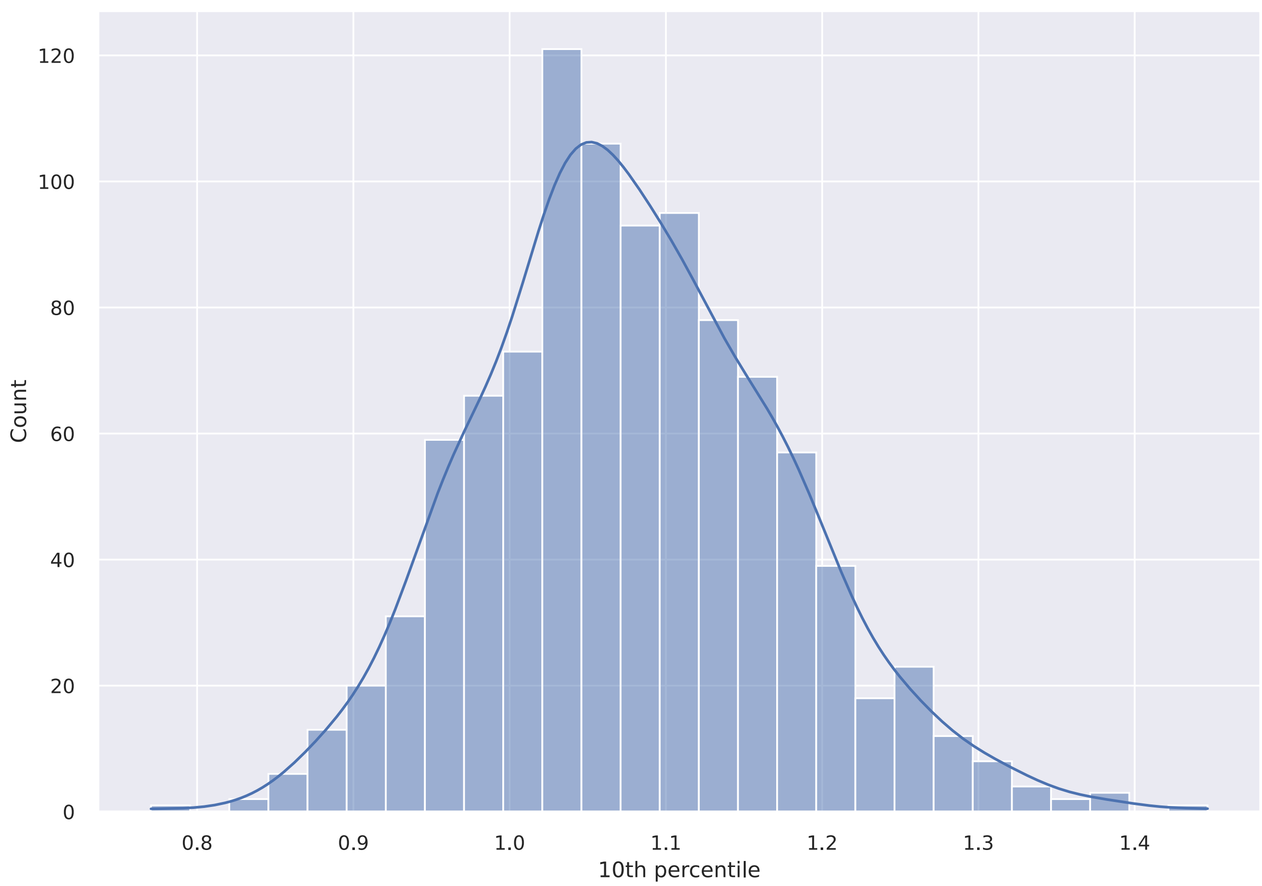
	10th percentile	mean	90th percentile
count	1000.000000	1000.000000	1000.000000
mean	1.078263	1.028802	1.007314
std	0.096703	0.057424	0.088951
min	0.770488	0.861009	0.695470
25%	1.015695	0.991036	0.947840
50%	1.071270	1.026426	1.004418
75%	1.141484	1.064210	1.066839
max	1.446643	1.270942	1.317118

histogram

10th percentile

```
sns.histplot(data=result["10th percentile"], kde=True)
```

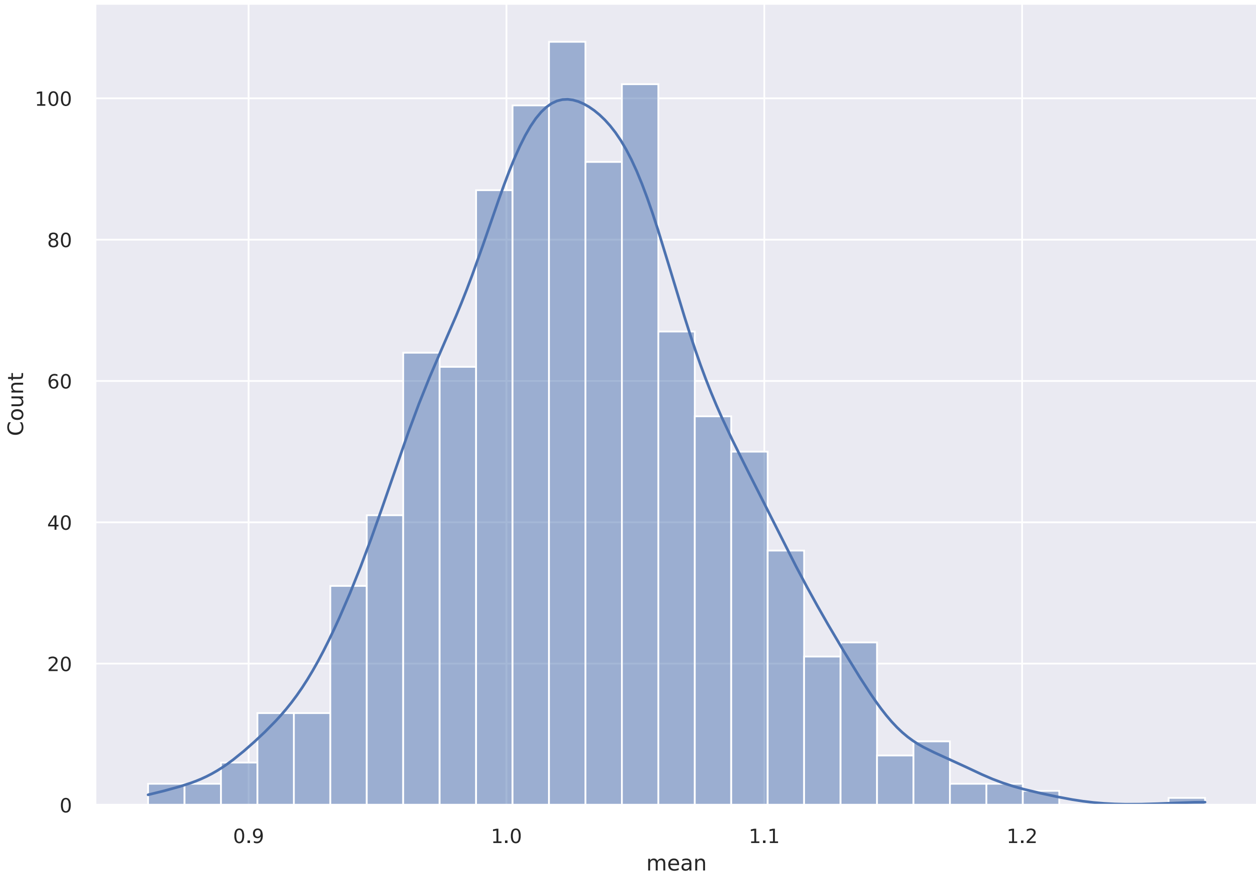
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4ff900cd0>
```



mean

```
sns.histplot(data=result["mean"], kde=True)
```

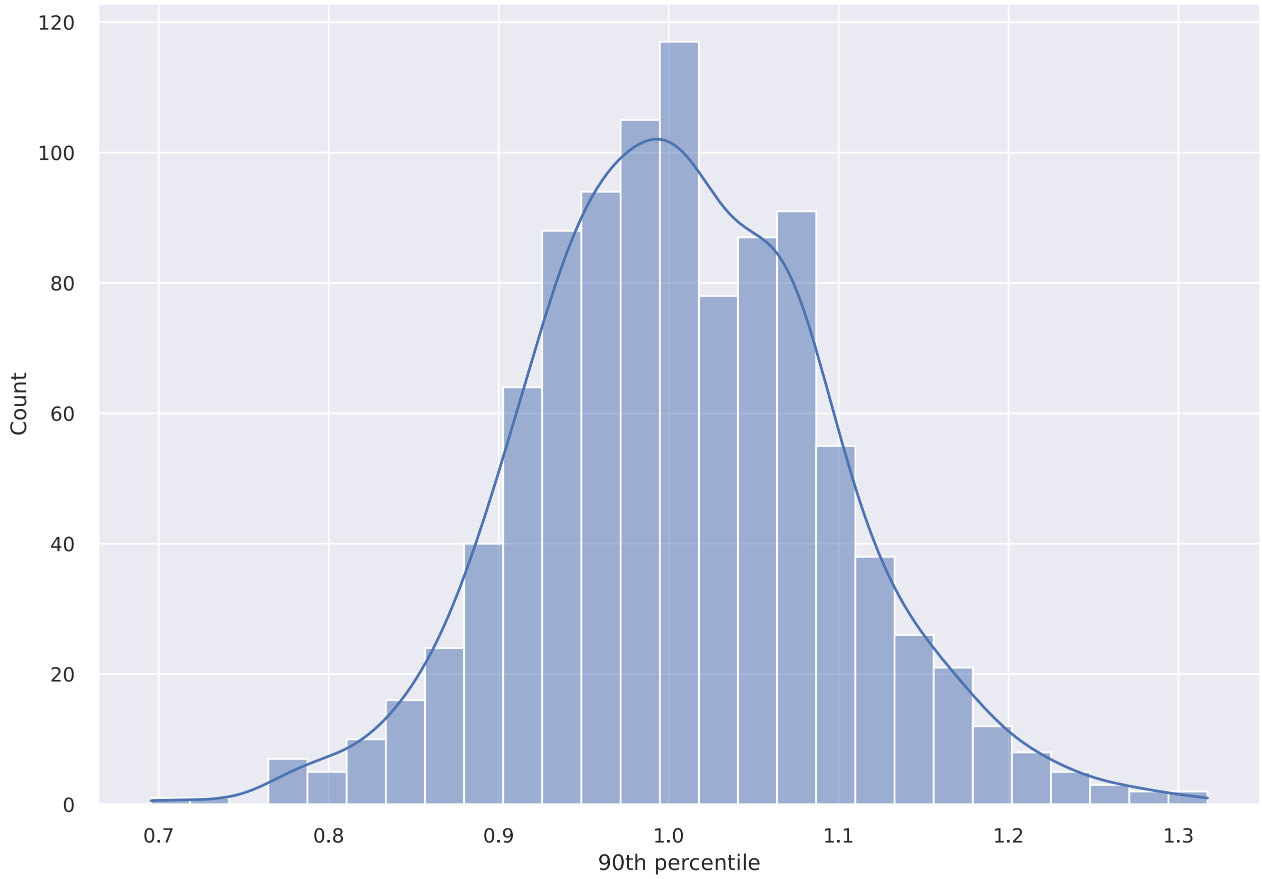
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fea2a890>
```



90th percentile

```
sns.histplot(data=result["90th percentile"], kde=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fe8d03d0>
```



$\mu_1=0.7, \sigma_1^2=0.08$, $\mu_2=0.85, \sigma_2^2=0.09$

```python
# 固定seed
np.random.seed(seed)

result = pd.DataFrame(columns=["10th percentile", "mean", "90th percentile"])

for _ in range(1000):
    # 第一組數據
    mu, sigma = lognorm_params(0.7, np.sqrt(0.08))
    random_one = np.random.lognormal(mean=mu, sigma=sigma, size=100)
    # 第二組數據
    mu, sigma = lognorm_params(0.85, np.sqrt(0.09))
    random_two = np.random.lognormal(mean=mu, sigma=sigma, size=100)

    result = result.append({"10th percentile": np.percentile(random_one, 10) / np.percentile(random_two, 10),
                            "mean": np.mean(random_one) / np.mean(random_two),
                            "90th percentile": np.percentile(random_one, 90) / np.percentile(random_two, 90)},
                           ignore_index=True)

pd.DataFrame.from_dict(result).describe()
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

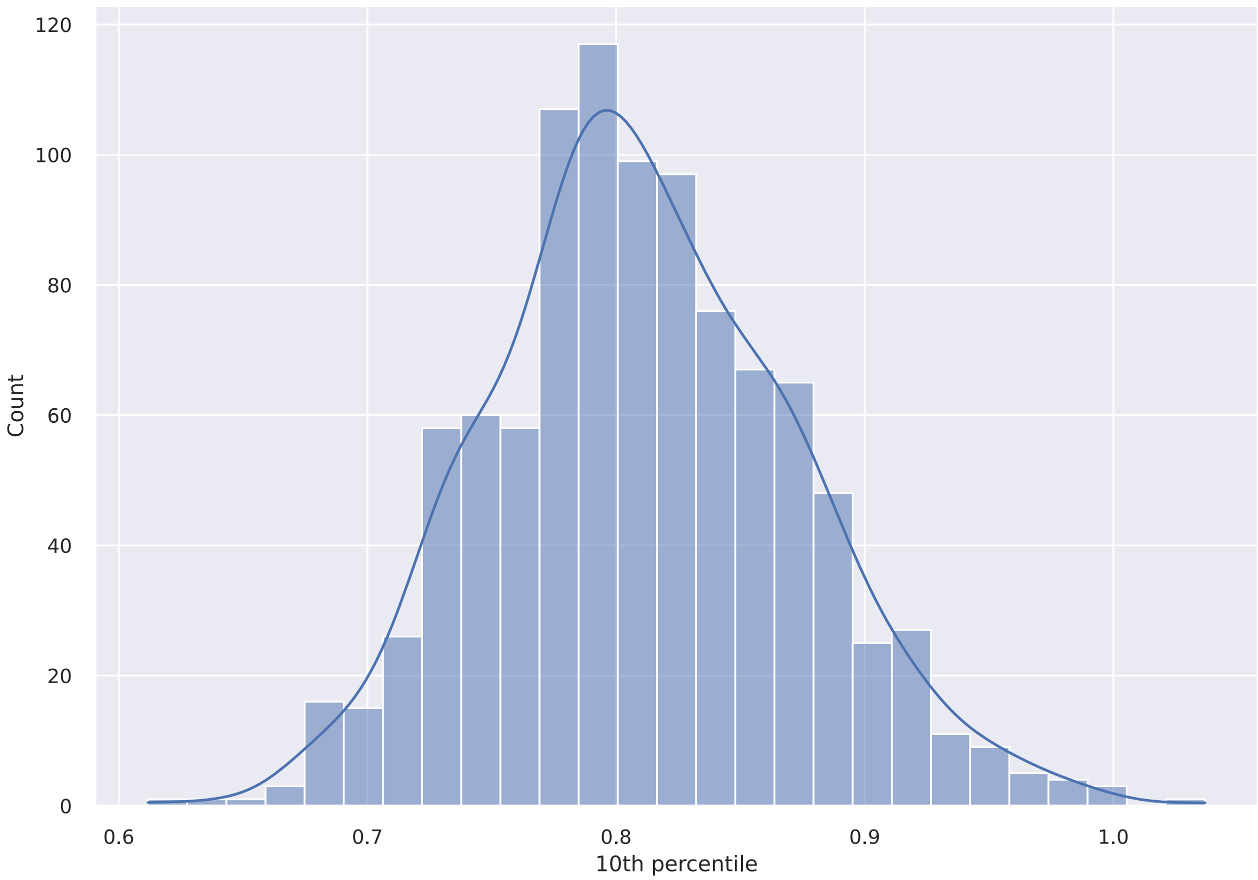
	10th percentile	mean	90th percentile
count	1000.000000	1000.000000	1000.000000
mean	0.810661	0.849853	0.877196
std	0.061378	0.039661	0.065507
min	0.611772	0.734970	0.643090
25%	0.771076	0.824798	0.833706
50%	0.806426	0.848944	0.875609
75%	0.851925	0.874312	0.921566
max	1.036868	1.020202	1.103631

histogram

10th percentile

```
sns.histplot(data=result["10th percentile"], kde=True)
```

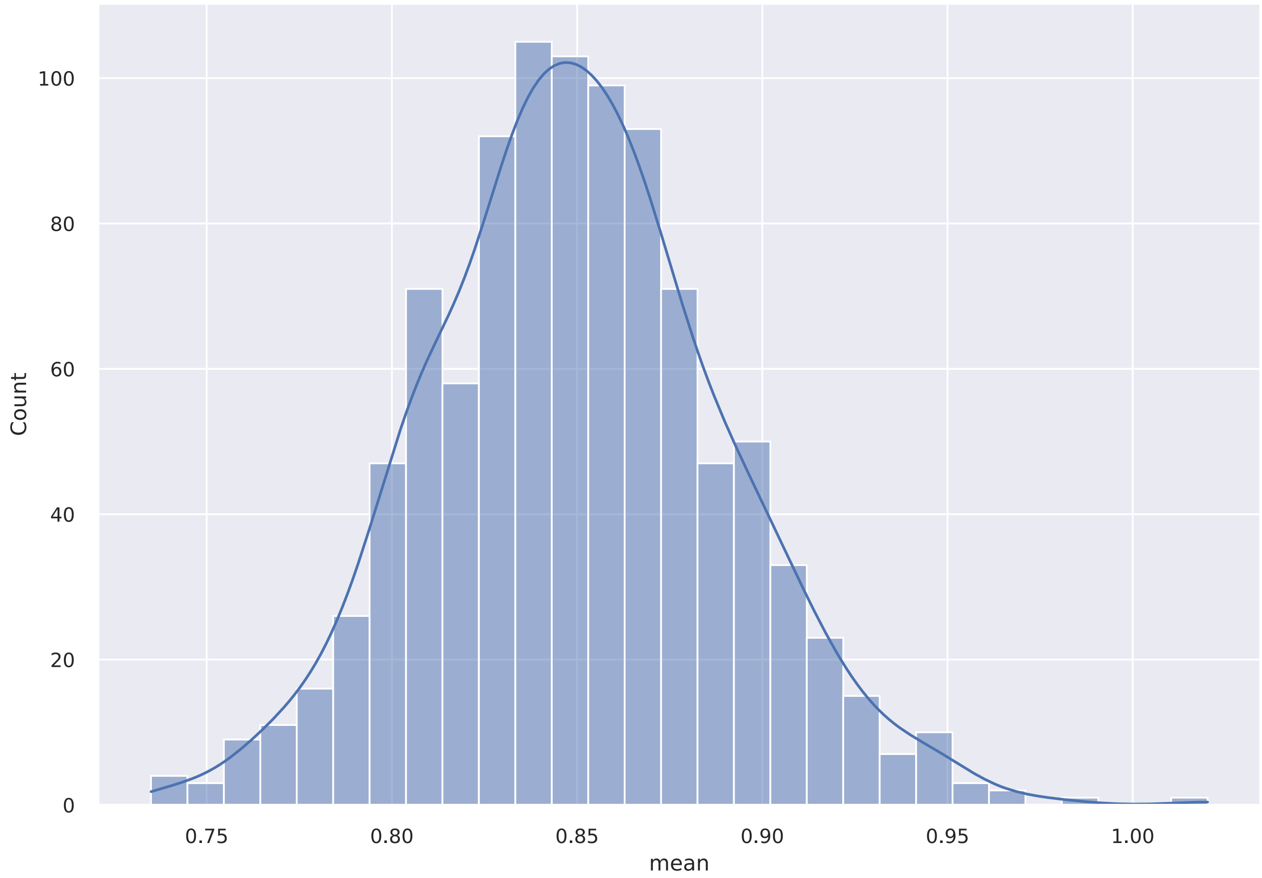
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fea68ed0>
```



mean

```
sns.histplot(data=result["mean"], kde=True)
```

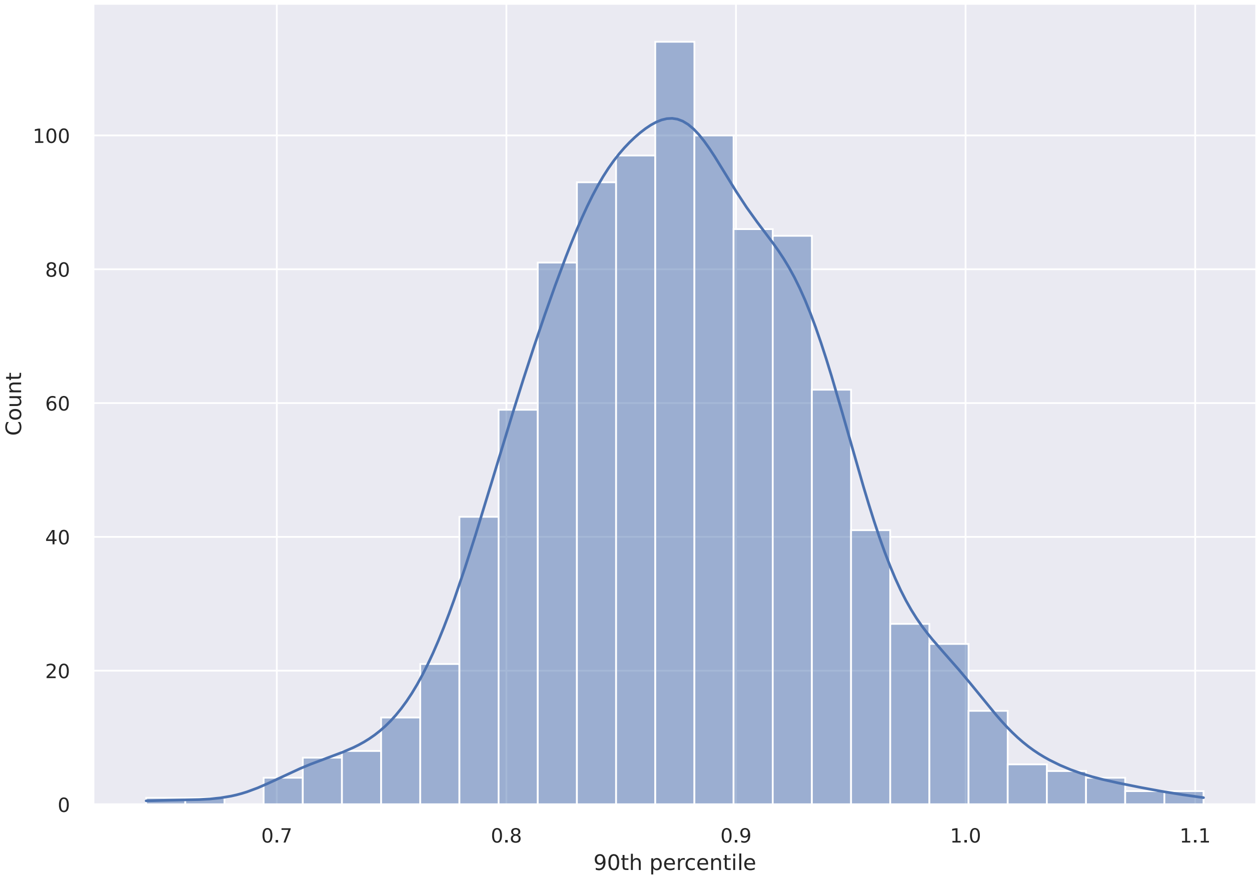
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fe7ec110>
```



90th percentile

```
sns.histplot(data=result["90th percentile"], kde=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff4fe696210>
```



100
80
60
40
20
0
Count
0.7
0.8
0.9
1.0
1.1
90th percentile