

Additional Files: Mathematical Proofs of Optimization and Related Codes



APPENDIX A

The Lagrangian function for optimization problem is:

$$\mathcal{L} = y - \lambda(w_1S + w_2I + w_3P + w_4N - m)$$

$$\mathcal{L} = (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}} - \lambda(w_1S + w_2I + w_3P + w_4N - m)$$

The first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial S} = (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} S^{\alpha-1} - \lambda w_1 = 0 \quad (1)$$

$$\frac{\partial \mathcal{L}}{\partial I} = (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} I^{\alpha-1} - \lambda w_2 = 0 \quad (2)$$

$$\frac{\partial \mathcal{L}}{\partial N} = (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} N^{\alpha-1} - \lambda w_3 = 0 \quad (3)$$

$$\frac{\partial \mathcal{L}}{\partial I} = (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} P^{\alpha-1} - \lambda w_3 = 0 \quad (4)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = -(w_1S + w_2I + w_3P + w_4N - m) = 0 \quad (5)$$

Dividing (18),(19),(20) by (17)

$$\frac{w_2}{w_1} = \left(\frac{I}{S}\right)^{\alpha-1}$$

Similar way

$$I = \alpha^{-1} \sqrt[\alpha]{\frac{w_2}{w_1} S}$$

$$P = \alpha^{-1} \sqrt[\alpha]{\frac{w_3}{w_1} S}$$

$$N = \alpha^{-1} \sqrt[\alpha]{\frac{w_4}{w_1} S}$$

Substituting these values in equation (21)

$$w_1S + W_2 \alpha^{-1} \sqrt[\alpha]{\frac{w_2}{w_1} S} + W_3 \alpha^{-1} \sqrt[\alpha]{\frac{w_3}{w_1} S} + w_4 \alpha^{-1} \sqrt[\alpha]{\frac{w_4}{w_1} S} - m = 0$$

$$S = \frac{mw_1 \alpha^{-1}}{w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}}} \quad (9)$$

Similarly

$$I = \frac{mw_2 \alpha^{-1}}{w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}}}$$

$$N = \frac{mw_3 \alpha^{-1}}{w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}}} \quad (11)$$

$$P = \frac{mw_4 \alpha^{-1}}{w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}}} \quad (12)$$

APPENDIX B

$$\mathcal{L} = w_1S + w_2I + w_3P + w_4N - \lambda((S^\alpha + I^\alpha + P^\alpha + N^\alpha) - y_{tar})$$

The first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial S} = w_1 - \lambda S^{\alpha-1} (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} = 0 \quad (13)$$

$$\frac{\partial \mathcal{L}}{\partial I} = w_2 - \lambda I^{\alpha-1} (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} = 0 \quad (14)$$

$$\frac{\partial \mathcal{L}}{\partial P} = w_3 - \lambda P^{\alpha-1} (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} = 0 \quad (15)$$

$$\frac{\partial \mathcal{L}}{\partial N} = w_4 - \lambda N^{\alpha-1} (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}-1} = 0 \quad (16)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = (S^\alpha + I^\alpha + P^\alpha + N^\alpha)^{\frac{1}{\alpha}} - y_{tar} = 0 \quad (17)$$

Dividing (30),(31),(32) by (29)

$$I = \alpha^{-1} \sqrt[\alpha]{\frac{w_2}{w_1} S}$$

$$P = \alpha^{-1} \sqrt[\alpha]{\frac{w_3}{w_1} S}$$

$$N = \alpha^{-1} \sqrt[\alpha]{\frac{w_4}{w_1} S} \quad (6)$$

Substituting the values in CES function

$$y_{tar} = (S^\alpha + (\frac{w_2}{w_1})^{\frac{\alpha}{\alpha-1}} S^\alpha) + (\frac{w_3}{w_1})^{\frac{\alpha}{\alpha-1}} S^\alpha + (\frac{w_4}{w_1})^{\frac{\alpha}{\alpha-1}} S^\alpha) \quad (7)$$

$$S = \frac{y_{tar} w_1^{\frac{1}{\alpha-1}}}{(w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}})^{\frac{1}{\alpha}}} \quad (8)$$

$$I = \frac{y_{tar} w_2^{\frac{1}{\alpha-1}}}{(w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}})^{\frac{1}{\alpha}}} \quad (9)$$

$$P = \frac{y_{tar} w_3^{\frac{1}{\alpha-1}}}{(w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}})^{\frac{1}{\alpha}}} \quad (10)$$

The cost function can be rewritten as :

$$c = \left(\frac{y_{tar}}{w_1^{\frac{\alpha}{\alpha-1}} + w_2^{\frac{\alpha}{\alpha-1}} + w_3^{\frac{\alpha}{\alpha-1}} + w_4^{\frac{\alpha}{\alpha-1}}} \right)^{\frac{1}{\alpha}-1}$$

APPENDIX C

The profit function is below

$$\text{Profit} = (S^\rho + I^\rho + P^\rho + N^\rho)^{\frac{1}{\rho}} - (w_1 S + w_2 I + w_3 P + w_4 N)$$

We want to maximize the profit subject to $w_1 S + w_2 I + w_3 P + w_4 N = c_{thresh}$

Using Lagrange multiplier

$$\mathcal{L} = (S^\rho + I^\rho + P^\rho + N^\rho)^{\frac{1}{\rho}} - (w_1 S + w_2 I + w_3 P + w_4 N) + \lambda(w_1 S + w_2 I + w_3 P + w_4 N - c_{thresh}) \quad (21)$$

$$\frac{\partial \mathcal{L}}{\partial S} = (S^\rho + I^\rho + P^\rho + N^\rho)^{\frac{1}{\rho}-1} S^{\rho-1} - w_1 + \lambda w_1 = 0 \quad (22)$$

$$\frac{\partial \mathcal{L}}{\partial I} = (S^\rho + I^\rho + P^\rho + N^\rho)^{\frac{1}{\rho}-1} I^{\rho-1} - w_2 + \lambda w_2 = 0 \quad (23)$$

$$\frac{\partial \mathcal{L}}{\partial P} = (S^\rho + I^\rho + P^\rho + N^\rho)^{\frac{1}{\rho}-1} P^{\rho-1} - w_3 + \lambda w_3 = 0 \quad (24)$$

$$\frac{\partial \mathcal{L}}{\partial N} = (S^\rho + I^\rho + P^\rho + N^\rho)^{\frac{1}{\rho}-1} N^{\rho-1} - w_4 + \lambda w_4 = 0 \quad (25)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = w_1 S + w_2 I + w_3 P + w_4 N - c_{thresh} = 0 \quad (26)$$

Comparing the λ value from equation (60) and (61). We can get

$$I = \frac{w_2}{w_1} S^{\frac{1}{\rho-1}}$$

Similar way other values are

$$P = \frac{w_3}{w_1} S^{\frac{1}{\rho-1}}$$

$$N = \frac{w_4}{w_1} S^{\frac{1}{\rho-1}}$$

Putting the values of I, P, N in equation (64)

$$w_1 + w_2 \frac{w_2^{\frac{1}{\rho-1}}}{w_1} S + w_3 \frac{w_3^{\frac{1}{\rho-1}}}{w_1} S + w_4 \frac{w_4^{\frac{1}{\rho-1}}}{w_1} S - c_{thresh} = 0$$

$$S = \frac{c_{thresh} w_1^{\frac{1}{\rho-1}}}{w_1^{\frac{\rho}{\rho-1}} + w_2^{\frac{\rho}{\rho-1}} + w_3^{\frac{\rho}{\rho-1}} + w_4^{\frac{\rho}{\rho-1}}}$$

Similar way other values are

$$I = \frac{c_{thresh} w_2^{\frac{1}{\rho-1}}}{w_1^{\frac{\rho}{\rho-1}} + w_2^{\frac{\rho}{\rho-1}} + w_3^{\frac{\rho}{\rho-1}} + w_4^{\frac{\rho}{\rho-1}}}$$

$$P = \frac{c_{thresh} w_3^{\frac{1}{\rho-1}}}{w_1^{\frac{\rho}{\rho-1}} + w_2^{\frac{\rho}{\rho-1}} + w_3^{\frac{\rho}{\rho-1}} + w_4^{\frac{\rho}{\rho-1}}}$$

$$N = \frac{c_{thresh} w_4^{\frac{1}{\rho-1}}}{w_1^{\frac{\rho}{\rho-1}} + w_2^{\frac{\rho}{\rho-1}} + w_3^{\frac{\rho}{\rho-1}} + w_4^{\frac{\rho}{\rho-1}}}$$

APPENDIX D

CES function

$$\begin{aligned} y &= (K^\rho + L^\rho)^{\frac{1}{\rho}} \\ \frac{\partial y}{\partial K} &= \frac{1}{\rho} (K^\rho + L^\rho)^{\frac{1}{\rho}-1} \rho K^{\rho-1} \\ \frac{\partial y}{\partial L} &= \frac{1}{\rho} (K^\rho + L^\rho)^{\frac{1}{\rho}-1} \rho L^{\rho-1} \\ \frac{\partial y}{\partial K \partial L} &= \rho K^{\rho-1} L^{\rho-1} (K^\rho + L^\rho)^{\frac{1}{\rho}-2} \\ \frac{\partial y}{\partial L \partial K} &= \rho K^{\rho-1} L^{\rho-1} (K^\rho + L^\rho)^{\frac{1}{\rho}-2} \\ \frac{\partial^2 y}{\partial^2 K} &= \rho(K^\rho - 1)^2 (K^\rho + L^\rho)^{\frac{1}{\rho}-2} + (\rho - 1) K^{\rho-2} (K^\rho + L^\rho)^{\frac{1}{\rho}-1} \\ \frac{\partial^2 y}{\partial^2 L} &= \rho(L^{\rho-1})^2 (K^\rho + L^\rho)^{\frac{1}{\rho}-2} + (\rho - 1) L^{\rho-2} (K^\rho + L^\rho)^{\frac{1}{\rho}-1} \end{aligned}$$

Hessian Matrix

$$\begin{bmatrix} \rho(K^\rho - 1)^2 (K^\rho + L^\rho)^{\frac{1}{\rho}-2} + (\rho - 1) K^{\rho-2} (K^\rho + L^\rho)^{\frac{1}{\rho}-1} & \rho K^{\rho-1} L^{\rho-1} (K^\rho + L^\rho)^{\frac{1}{\rho}-2} \\ \rho K^{\rho-1} L^{\rho-1} (K^\rho + L^\rho)^{\frac{1}{\rho}-2} & \rho(L^{\rho-1})^2 (K^\rho + L^\rho)^{\frac{1}{\rho}-2} + (\rho - 1) L^{\rho-2} (K^\rho + L^\rho)^{\frac{1}{\rho}-1} \end{bmatrix}$$

$$\Delta_1 = (K^\rho + L^\rho)^{\frac{1}{\rho}-1} K^{\rho-1} \left(\frac{\rho K^{\rho-1}}{K^\rho + L^\rho} + \frac{\rho-1}{K} \right)$$

As $K, L, \rho > 0$ $\Delta_1 > 0$

$$\Delta_2 = \rho(\rho - 1)(K^{\rho-1})^2 (L^{\rho-2})(K^\rho + L^\rho)^{\frac{2}{\rho}-3} + \rho(\rho - 1)(L^{\rho-1})^2 (K^{\rho-2})(K^\rho + L^\rho)^{\frac{2}{\rho}-3} + (\rho - 1)^2 (K^{\rho-2})(L^{\rho-2})(K^\rho + L^\rho)^{\frac{2}{\rho}-2}$$

$\Delta_2 \geq 0$ in case $\rho \geq 1$

As $\Delta_1 \geq 0$ and $\Delta_2 \geq 0$ in case $\rho \geq 1$. It will produce concave graph.

When $\rho < 1$, $\Delta_1 \geq 0$ and $\Delta_2 \leq 0$.

It is neither concave or convex.

APPENDIX E

In this appendix, we are going to explain the reason why Δ_1 from previous appendix is always positive.

Considering δ_1 value again:

$$\Delta_1 = (K^\rho + L^\rho)^{\frac{1}{\rho}-1} K^{\rho-1} \left(\frac{\rho K^{\rho-1}}{K^\rho + L^\rho} + \frac{\rho-1}{K} \right)$$

Δ_1 will be negative if below two conditions are satisfied.

1) $\rho < 1$

$$2) \frac{\rho-1}{K} \geq \frac{\rho K^{\rho-1}}{K^\rho + L^\rho}$$

$$\begin{aligned}
\frac{\rho-1}{K} &\geq \frac{\rho K^{\rho-1}}{K^{\rho} + L^{\rho}} \\
\Rightarrow (\rho-1)(K^{\rho} + L^{\rho}) &\geq \rho K^{\rho} \\
\Rightarrow \frac{\rho-1}{\rho} &\geq \frac{K^{\rho}}{K^{\rho} + L^{\rho}} \\
\Rightarrow 1 - \frac{1}{\rho} &\geq \frac{K^{\rho}}{K^{\rho} + L^{\rho}} \\
\Rightarrow 1 - \frac{K^{\rho}}{K^{\rho} + L^{\rho}} &\geq \frac{1}{\rho} \\
\Rightarrow \frac{L^{\rho}}{K^{\rho} + L^{\rho}} &\geq \frac{1}{\rho} \\
\Rightarrow \rho L^{\rho} &\geq K^{\rho} + L^{\rho} \\
\Rightarrow (\rho-1) &\geq \frac{K^{\rho}}{L^{\rho}} \\
\Rightarrow \rho-1 &\geq \left(\frac{K}{L}\right)^{\rho}
\end{aligned}$$

As $K, L > 0$, hence $\left(\frac{K}{L}\right)^{\rho}$ will be always positive.

$$\begin{aligned}
(\rho-1) &> 0 \\
\Rightarrow \rho &> 1
\end{aligned}$$

Which is contradicting the first condition $\rho < 1$.
Hence Δ_1 will be always positive.

APPENDIX F

Below is the proposed model, which we want to fit using least square approach.

$$(k_1^r + k_2^r)^{\frac{1}{r}}$$

Matlab code when $r < 1$ The datasets k_1, k_2 and observed data ydata are given as

$$\begin{aligned}
k_2 &= [5, 5, 10, 10, 10, 15, 15, 15, 20, 20, 20, 30, 30, 30, 40, 40, 40] \\
k_1 &= [62, 65, 62, 60, 65, 55, 45, 47, 50, 52, 55, 56, 57, 58, 59, 60, 60] \\
ydata &= [19511.9, 20038.22, 26579.25, 26108.41, 27274.01, \\
&30038.95, 27008.5, 27635.78, 32723.23, 33401.89, 34399.27, \\
&42176.36, 42563.18, 42947.06, 49839.75, 50268.74, 50268.74]
\end{aligned}$$

The function which is needed to pass in the matlab lsqnonlin function is $fun = @(r)(k_1^r + k_2^r)^{\frac{1}{r}} - ydata$. In the case of without constraints, no upper and lower bound of r need to pass in the function. We will assume a initial value for r as 0.4. Next calling the lsqnonlin function
 $x = lsqnonlin(fun, x_0)$
 $x = 0.1000$; So we obtained the least square r value as 0.1000. Say the upper bound for r is 0.9 and lower bound as 0.1. We will pass the same information in lsqnonlin function.

$$\begin{aligned}
x &= lsqnonlin(fun, x_0, 0, 0.9); \\
x &= 0.1000;
\end{aligned}$$

We get the same output as we have obtained without constraints.

Matlab code when $r > 1$

$$\begin{aligned}
k_2 &= [5, 5, 10, 10, 10, 15, 15, 15, 20, 20, 20, 30, 30, 30, 40, 40, 40] \\
k_1 &= [62, 65, 62, 60, 65, 55, 45, 47, 50, 52, 55, 56, 57, 58, 59, 60, 60] \\
ydata &= [65.5239, 68.5078, 69.5306, 67.5538, 72.4972, \\
&66.8546, 57.0674, 59.0214, 66.3455, 68.2907, 71.2122, 81.1220, \\
&82.0859, 83.0503, 93.1262, 94.0819, 94.0819] \\
fun &= @(r)(k_1^r + k_2^r)^{\frac{1}{r}} - ydata; \\
x_0 &= 1.4; \\
x &= lsqnonlin(fun, x_0) \\
x &= 1.1000;
\end{aligned}$$

Say the upper bound for r is 1.9 and lower bound as 1.

$$\begin{aligned}
x &= lsqnonlin(fun, x_0, 1, 1.9); \\
x &= 1.1000;
\end{aligned}$$

APPENDIX G

Code for Shapiro-Wilk goodness-of-fit test
Mupad command has been used to generate the code.

$$\begin{aligned}
data &:= [62, 65, 62, 60, 65, 55, 45, 47, 50, 52, 55, 56, 57, 58, 59, 60, 60] : \\
stats &:: swGOFT(data) \\
[PValue &= 0.4011881607, StatValue = 0.9463348025] \\
data &:= [78, 60, 55, 44, 75, 62, 55, 49, 55, 57, 65, 46, 77, 68, 59, 48, 60] : \\
stats &:: swGOFT(data) \\
[PValue &= 0.3841895654, StatValue = 0.9451314104] \\
data &:= [5, 5, 10, 10, 10, 15, 15, 15, 20, 20, 20, 30, 30, 30, 40, 40, 40] : \\
stats &:: swGOFT(data) \\
data &:= [15, 35, 18, 20, 30, 15, 25, 18, 25, 24, 35, 38, 27, 32, 16, 10, 30] : \\
stats &:: swGOFT(data) \\
[PValue &= 0.6499020509, StatValue = 0.9609763672]
\end{aligned}$$

0.05 is the threshold of pvalue. As all the observed Pvalue are greater than the threshold. The null hypothesis is accepted and datasets are belong to normal distribution. Code for chi-square
 $data = [62, 65, 62, 60, 65, 55, 45, 47, 50, 52, 55, 56, 57, 58, 59, 60, 60];$
 $h = \text{chi2gof}(data);$
In case of normal distribution $h=0$ otherwise $h=1$.

APPENDIX H

The matlab fmincon code when $\rho < 1$:

```
A = [1; -1];
b = [0.9; -0.1];
x0 = [0.4];
[x, fval] = fmincon(@myCES, x0, A, b)
function f = myCES(x)
pow = 1/x(1);
f = -(62x(1) + 5x(1)).pow;
end
```

The matlab fmincon code when $\rho > 1$:

```
A = [1; -1];
b = [1.9; -1.1];
x0 = [0.4];
[x, fval] = fmincon(@myCES, x0, A, b)
function f = myCES(x)
pow = 1/x(1);
f = -(62x(1) + 5x(1)).pow;
end
```